Bio-inspired Algorithms for Tactile Control of Dexterous Manipulation

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Abstract—Few years old children lift and manipulate unfamiliar objects more dexterously than today's robots. Thus, robotics researchers increasingly agree that ideas from biology can strongly benefit the design of autonomous robots. In this paper, bio-inspired algorithms for lifting unfamiliar objects with grasp stability and human-like behavior are presented. In these algorithms, simulated human tactile afferent responses, drive the control of the grip and load forces, and signal important events in the lifting task. The presented model and algorithms follow closely the human behavior in a lifting task, as revealed by neurophysiological studies of human dexterous manipulation.

I. INTRODUCTION

Typically, when robots manipulate objects, they must do so with a predetermined grasp force. By contrast, humans are skilled at manipulating objects with grasp forces maintained only slightly above the minimum required to prevent slipping. The term grasp stability entails both the prevention of accidental slips and the prevention of excessive fingertip forces. The goal of the control model presented in this paper is to lift unfamiliar objects with grasp stability and human-like behavior. To achieve this goal, a control model and algorithms, emulating each one of the human lifting phases, need to be designed. The control of the grip and load forces at each phase is driven by signals that simulate the responses of the human tactile afferents.

There are previous works in robotics on segmenting a manipulative task inspired by the human model. In [1] the authors followed the human model, and partitioned the task in pre-contact, loading, manipulation, unloading, and post-contact phases. They used force sensors and accelerometers to detect phase changes. Cutkosky proposed an event-based language for dextrous manipulation, where the different phases of manipulation are divided by events [2]. However, these authors just segmented the manipulative task at a high level, without providing detailed control algorithms for each one of the manipulative phases.

II. TECHNICAL APPROACH

There are four types of afferents in the glabrous skin of the human hand: FA-I, SA-I, SA-II and FA-II. All together, there are approximately 17,000 mechanoreceptors in the glabrous skin of each hand. The SA I and SA II units are referred to as slowly adapting afferents, which means that they show a sustained discharge in the presence of ongoing stimuli. In contrast, the fast adapting afferents, FA I and FA II, fire rapidly when a stimulus is presented (or removed) and then fall silent when the stimulation cease to change.

Israelsson [3] designed a computational simulator of the responses of the tactile afferents from the glabrous skin. Using as input 3-D force signals, her simulator gives as output simulated tactile afferent responses.

In humans, once the fingertips have reached the object, an episode of lifting and lowering an object from and to a table top involves: (a) Preload phase: using the fingers to apply force perpendicular to the objects surface at the points of contact of the fingers with the object; (b) Load phase: is characterized by a parallel increase in the grip and load forces; (c) Transitional phase: it begins when the load force has overcome the weight of the object, and it ends when the object arrives into the desired vertical position; (d) Static phase: where the object is held in the air by fairly constant grip and load forces; (e) Controlled lowering phase: by reducing the load forces to allow the objects position to slowly approach the tabletop; (f) Release phase: parallel decreasing the grip and load forces due to the release of the object. Short-lasting, specific patterns of sensory activity of the different types of tactile afferents seem to trigger the transition between the different phases of a task [4].

The method followed in this article has been to design a control model inspired by the human strategy to lift objects, to simulate human tactile afferents from 3D force values using the method designed by Israelsson [3], and to design algorithms for each one of the different phases of the manipulation strongly inspired by neurophysiological studies. To validate the model, a finite element software was used to model different objects and two fingers lifting the object.

III. CONTROL MODEL AND ALGORITHMS

Johansson proposed a conceptual model for the application of grip forces and load forces in a human lifting task [5]. Briefly, vision provides information on object position, object size, and object shape. Based on visual estimates of weight and friction, a set of tactile responses is predicted to guide planning for the application of initial grip force to the object. Tactile perceptions of weight and texture are fed back and compared to the predicted weight and texture. The mismatch is used to update memory representations of weight and texture for a specific object appearance. This memory is assumed to be retrieved on later occasions to guide anticipatory application of forces [6]. The control model of this paper, takes inspiration in this conceptual model of human dexterous manipulation, to propose a detailed computational control model for robotic dexterous manipulation.
The general design of the control system is shown in fig. 1. It is assumed that there is a vision module that provides information about the properties of the object needed by the force control module. If the object to be taken is the last object that has been manipulated, the force control module asks for information to the short term memory. Otherwise, it asks to the long term memory. With this dual memory, the controller has more dexterity to manipulate objects, because preserving the force ratio and the weight of the last manipulated object, the controller does not need to calculate them again, if it is required to manipulate the same object in consecutive trials.

The force control module is at the core of the control system. This module controls the grip and load forces applied by the hand on the object. It also updates the values stored in the memories. Inside this module, algorithms were designed for each one of different phases observed in human dexterous manipulation, that follow closely the human behaviour observed by neurophysiologists in human dexterous manipulative tasks. The algorithms receive as input simulated human tactile afferents that guide the control of the grip and load forces. Artificial neural networks are also part of this module, and are used to estimate the friction, and to detect the incipient slips.

A. Force Control Module

The force control module is at the core of the control system. This module controls the grip and load forces applied by the hand on the object. It also updates the values stored in the memories.

The module is divided in sections that correspond to the different phases observed in human lifting tasks (section §II).

The following input variables are provided by the memories: force ratio on the thumb’s side $\rho_{t,\text{memory}}$, force ratio on the opposing fingers’ side $\rho_{o,\text{memory}}$, material density on the thumb’s side $\rho_{t}$, material density on the opposing fingers’ side $\rho_{o}$, force ratio of the last object $\rho_{\text{last}}$, weight of the last object $\text{Weight}_{\text{last}}$. The following input variables are provided by the Vision Module: estimated size of the object $\text{Size}$, surface angle $\text{SurfaceAngle}$, last object $\text{LastObject}$, material of the object $\text{Material}$.

1) Initialization

$$
GF \leftarrow 0; \quad LF \leftarrow 0;
$$

if LastObject = True then

$$
\text{Weight} \leftarrow \text{Weight}_{\text{last}};
$$

else

$$
\text{Weight} \leftarrow \text{Size} \times \frac{\text{Density}_{o} + \text{Density}_{t}}{2} \times g;
$$

end

Algorithm 1: Initialization

First, the grip and load forces are initialized to zero. Then, the weight of the object is estimated based on the size and the density returned by the vision module. If the object has an unknown material a medium value is used as the density of the material (a medium value is the medium between the maximum and minimum values allowed by the simulator).

2) Preload phase

In humans, the friction coefficient predominantly determines the minimum force ratio required to prevent slips. The initial responses in the FA-I afferents are considered responsible for the initial adjustment to a new frictional condition. The more slippery the material, the higher the FA I discharge rate is at the preload phase. The required force ratio to grip the object with grasp stability is known when the object is held in the air, at the static phase. Thus, it would be useful to create an association between the required force ratio to grip the object with grasp stability, and the initial pattern of FA I signals received. To create this association a supervised artificial neural network is used. At the initial state, the control system has no knowledge about the required force ratio associated to any FA I pattern. After some experiments, the system learns the association between the past FA I patterns and the corresponding force ratios. When a new FA I pattern is received, the system maps this pattern into the neural network, and gets an initial force ratio. If this force ratio produces slips, then the system will train the neural network to introduce the new pattern and its required force ratio association.

The preload phase is modeled in Algorithm 2. First, in order to build a representative pattern of FA I signals, the grip force is increased until a significant deformation of the finger is reached. By significant deformation we mean that the finger-object contact area is enough to grasp the object. Next, the required force ratio $\rho$ to achieve grasp stability is estimated as a function of the initial FA I responses, and the force ratio recorded in memory for the material of the object. If there is no record in the memory for that material, the force ratio is estimated based on the initial responses of the FA I afferents. This initial value of
the force ratio will be improved with the detection of slips in the next phases. To estimate the force ratio from the initial FA I responses, an artificial neural network (ANN) is used, that receives as input the FA I pattern produced during the initial deformation of the finger. A factor $0.5 < k < 1$ multiplies the ANN force ratio estimation, and the factor $(1 - k)$ multiplies the force ratio recalled from memory. Finally, the Shape Adaptation function adapts the force ratio $\rho$ to the curvature of the grip surface.

3) **Loading phase**

In humans, during the loading phase, the grip and load forces increase in parallel. This parallel increase terminates shortly after the object starts to move. Memory information based on previous experiences with the weight of the current object is used to parameterize the force output in anticipation of the weight of the object. Consequently, with an unexpected change to a lighter weight, the load and grip force rates are excessively high when the load force suddenly overcomes the force of gravity. However, an abruptly triggered termination of the muscle commands driving the load phase takes place some 80-110 ms after lift-off [7]. Burst responses in FA II afferents, which effectively indicate that the object has started to move, are most likely used to trigger this. But the delays in the control loop due to receptor and effector delays, axonal conductances, and Central Nervous System (CNS) processing delays are still long enough to cause a pronounced position overshoot. If the object is heavier than expected and the lift-off does not occur at the predicted load force, the absence of motion is indicated through the lack of a transient sensory response at the expected moment of lift-off. In this case, the CNS uses the absence of the expected sensory signal to quickly initiate a new control mode. This is characterized by slow, discontinuous increases in force that, in effect, probe for the lift-off. This control mode continues until somatosensory information confirming movement is eventually obtained. Hence, whether the weight is correctly anticipated or not, somatosensory signals apparently trigger the termination of the load phase and presumably simultaneously update the memory system representation of the weight of the object. Indeed, with erroneous weight anticipation, only one lift is typically required to efficiently update the weight-related memory system. As regards the lifting speed, to get a predictable, smooth and critically damped vertical lifting movement, the lifting drive must be decreased and appropriately adjusted to match the weight of the object before the moment of lift-off. In fact, with an adequately programmed lift, the first time derivative of the grip and load forces have their maximum when the load force matches about half the weight of the object; the force rates are reduced prior to lift-off to harmonize with the expected weight [5].

### Algorithm 2: Preload phase

```latex
\begin{algorithm}
\caption{Preload phase}
\begin{algorithmic}
\While {\text{Finger deformation} \leq \text{Significant deformation}}
\Do in Parallel (Increase $GF$, Record FA I signals)
\End
\If {$\rho_1^{\text{memory}} = \text{NULL}$}
\State $\rho_t \leftarrow \text{ANN}(\text{FA I pattern})_t$;
\Else
\State $\rho_t \leftarrow k \times \text{ANN}(\text{FA I pattern})_t + (1 - k) \times \rho_t^{\text{memory}}$;
\End
\EndIf
\If {$\rho_o^{\text{memory}} = \text{NULL}$}
\State $\rho_o \leftarrow \text{ANN}(\text{FA I pattern})_o$;
\Else
\State $\rho_o \leftarrow k \times \text{ANN}(\text{FA I pattern})_o + (1 - k) \times \rho_o^{\text{memory}}$;
\End
\EndIf
\State \text{Shape adaptation}($\rho_t$, Surface angle);
\State \text{Shape adaptation}($\rho_o$, Surface angle);
\end{algorithmic}
\end{algorithm}
```

### Algorithm 3: Loading Phase Algorithm

The loading phase is modeled in Algorithm 3. A preliminary version of this algorithm has been outlined by the author at [8]. At this phase, the forces are increased in parallel preserving the force ratio (i.e., $LF_t \leq \frac{GF}{2}/\rho_t$ and $LF_o \leq \frac{GF}{2}/\rho_o$), until the object lifts off. The initial force ratio is the force ratio estimated at the preload phase. If slips were detected, then the force ratio is corrected and updated, to stop the slips. At the first loop, the load force is increased to make it proportional with the grip force according to the force ratio. Next, at the second loop, the grip and load forces are increased in parallel, until the load force reaches
the estimated weight of the object, or the object lifts off. Finally, if the estimated weight is lesser than the actual weight, the third loop is entered. In this loop, burst parallel increases of the grip and load forces are made until the object lifts off.

In the model, the lift-off and slip events are signalled by simulated afferent responses, which correspond with the tactile afferent responses that signal these events in humans.

The lift-off is detected by the presence of FA II responses, and the absence of FA I and SA I responses. The lift off detection is modeled in function Test Lift-off.

```
if Strong FA II signals and FA I and SA I signals near null then
  Lift Off ← True
end
```

Function Test Lift-off

In humans, the slips are signalled by sudden changes in the load force between the thumb and the opposing fingers, and by discharges of FA I, SA I, and eventually FA II mecanoreceptors. The slip events fire force ratio corrections. If there are responses of the FA I, SA I and FA II afferents, then the force ratio upgrade will be larger than if there were only responses of the FA I and SA I afferents (i.e., an incipient slip). If there are only responses of the FA II units, then the vibration will not be recognized as slip, and therefore it will not trigger upgrades of the force ratio [9]. In the model, an artificial neural network is used to estimate the intensity of the slip. The neural network receives as input the FA I, SA I, and FA II signals, and gives as output the intensity of the slip. The intensity of the slip indicates the percentage of contact nodes that are slipping, and it is measured as a number in the interval [0...1]. The test slip function checks if there are slip events. If there were significant slip events it calls the slip correction function:

```
Slip Intensity ← ANN (FA I, SA I, FA II);
if Slip Intensity > Threshold then
  Call Slip Correction (GF, LF t, LF o, ρ t, ρ o, Slip Intensity);
end
```

Function Test Slip

The function Slip Correction is used to stop the slip, and to adjust the force ratio based on the intensity of the slip:

Fagergren et al. [10] studied human behavior, and found that the best control strategy to stop slips was a burst increase of the grip force. Therefore, this same strategy is used in the above function to stop slips. First, a strong increase of the grip force is applied to stop the slip. Next, the grip force is decreased to an appropriate value. A factor that depends on the slip intensity, multiplies the grip force adjustment. Finally, the force ratio is corrected. When grasping objects, humans readily identify the minimum force required to prevent slipping and maintain a safety margin of 10% - 30% [11]. Thus, in the model, a safety margin is added to the force ratio also.

4) Transitional phase

```
while Height of Hand < Desired Height do
  Do in Parallel (Test Slip under Gravity,
                    Parallel increase of the GF and LF at low velocity)
end
```

Algorithm 4: Transitional phase

At the transitional phase, the hand is risen until it reaches the desired height. First, the grip and load forces are increased in parallel until the desired height is reached. In humans, it is observed a grip force increase at the end of the parallel coordination of the forces during lifting. Thus, just before stopping the upward movement, the grip force is increased by a factor \(k > 1\), to prevent that the object would slip out by the sudden stop of the upward movement. Then, the arm is stopped. Finally, the previous value of the grip force is restored.

In humans, responses originated from small slips localized to only a part of the skin area in contact with the object and in the absence of detectable vibrations events, are only observed in the FA-I and SA-I units, and are often followed by small force ratio changes [12]. Such slips, called localized frictional slips, also trigger appropriate grip force adjustments for grasp stability when an object is held in the air. Thus, when the object is in the air, the function Test Slip under Gravity, is used to estimate the slip intensity and, if required, to make the force corrections. This function is similar to the Test Slip function previously described, but the artificial neural network (ANN) only receives as input FA I and SA I signals.
5) Static phase
In the static phase the object is held in the air and it is moved horizontally towards the new position. The load force on a hand-held object is determined by the weight of the object \((mg)\) when held stationary. When the grasped object is moved, additional loading is required to accelerate the object \((ma)\). Thus, the total load force required is \(mg + ma\).

\[
GF \leftarrow GF + m \times a \times (\rho_t + \rho_o);
\]

\[
\text{while } \text{Goal Position} = \text{False } \text{do}
\]
\[
\quad \text{Do in Parallel (Test Slip under Gravity, Move object horizontally)}
\]
\[
\text{end}
\]
\[
GF \leftarrow GF - m \times a \times (\rho_t + \rho_o);
\]

Algorithm 5: Static phase

6) Replacement and Unloading phase
At this phase the object is moved downward until it contacts the table top. Then it is released.

\[
\text{Weight} \leftarrow LF;
\]
\[
\text{repeat} \text{Do in Parallel (Test Slip under Gravity, Move object horizontally)}
\]
\[
\text{until Object Release;}
\]
\[
\quad \text{if Material}_i = \text{Material}_o \text{ then}
\]
\[
\quad \quad \text{Density} \leftarrow \frac{\text{Weight}}{g} / \text{Size};
\]
\[
\quad \text{else}
\]
\[
\quad \quad \text{Density} \leftarrow \text{Null;}
\]
\[
\text{end}
\]
\[
\text{Update memory (Material}_i, \text{Material}_o, \text{Density, } \rho_t, \rho_o, \text{Weight);}
\]

Algorithm 6: Replacement and Unloading phase

First, the load force value is saved into the \text{Weight} variable. The weight is saved at this moment, because at this moment the object is held in the air and there is a stable load force. Next, the arm goes down until the object contacts the table. The contact table event is detected, as in humans, by a burst signal of simulated FA II afferents. Then, there is a sudden reduction of the load force, to set the object on the tabletop. In human manipulation, this reduction of the load force is about 20%; thus, \(k_{rel} \leq 0.8\). In humans, there is a short delay between the contact table event and the parallel decrease of the forces. Thus, a short delay follow the sudden reduction of the load force in the above algorithm, whose goal is to stabilize the object on the table. After this wait, follows a parallel decrease of the forces, that causes the release of the object. Finally, the memory is updated.

IV. Experiments

Finite element method (FEM) was used to build 3-D simulations of two opposed fingers lifting planar objects (Fig. 2), and a finger pressing a planar surface. Finite element code \text{MScMarc} release 2 was used.

![3-D FEM model of two fingers and a planar object.](image)

From the nodes of the FEM model, 3D force measures can be obtained. To simulate the tactile afferent responses from 3D force signals, software code provided by Anna Theorin (f. Israelsson), Benoni Edin, Lars Rådman, and Roland Johansson of Umeå University was adapted. Fig. 3 shows an overview of the developed software system.

![Block diagram of the software modules.](image)

In humans, grasp stability is achieved keeping the force ratio greater than the slip ratio plus a safety margin. The estimation of the friction coefficient and the detection of the incipient slipping, occupy a key role in the grasp stability mechanism. The slip ratio is predominantly determined by the coefficient of friction between the object and the fingers. Humans estimate the friction coefficient at the preload phase. This estimation of the friction coefficient is used by the central nervous system, to set the initial force ratio. Further adjustments to the force ratio in order to keep grasp stability are made during the manipulative task, based on the detection of slips. In particular, incipient slips are a precursor to the unwanted gross slip, and make it possible to sense the slip limit before it is reached.

Multilayer perceptrons with different numbers of units in the hidden layer were trained and tested, to estimate the friction coefficient and to detect the incipient slipping, using as input the simulated tactile afferents obtained from the simulated FEM experiments.

For the estimation of the friction coefficient, simulations of a finger pressing an object were performed, increasing the friction coefficient of the objects material in the FEM
model from 0.01 to 1.00 (with an step size of 0.005). As the experiment was repeated changing the friction coefficient from 0.01 to 1.00, with an step size of 0.005, 200 input patterns were generated. A random partition of this set was done, in which the 90 percent of the patterns was chosen as training set and the remaining 10 percent as testing set. Multilayer perceptrons with different numbers of units in the hidden layer were trained and tested, and a multilayer perceptron with 1 hidden layer of 3 neurons obtained the best performance. The final architecture of the neural network consisted of an input layer of 100 units, a hidden layer of 3 units, and an output layer of 1 unit. The final performance of the neural network was a mean squared error of the training set of 0.0025 and a mean absolute error of 0.0373. The mean squared error of the testing set was 0.0118 and its mean absolute error was 0.0853. As the maximum value of the target test set was 1.0, this result gives a relative error for the testing set of 8.53%. Further details of this experiment to estimate the friction coefficient can be found in [13]–[15].

For the detection of the incipient slipping, experiments with an object of weight 200 were made. Several simulated experiments were done changing the friction coefficient of the object from 0.50 to 0.90, and a total of 2100 input patterns were generated. A random partition of the input patterns set was done, in which the 90 percent of the patterns was chosen as training set and the remaining 10 percent as testing set. Different multilayer perceptrons were tested, and a multilayer perceptron with 1 hidden layer of 3 neurons obtained the best performance. The final architecture of the neural network consisted of an input layer of 38 units, a hidden layer of 3 units, and an output layer of 1 unit. The neural network was trained, and at the final state (46th epoch), the mean squared error of the training set was 5.5617e-004 and its mean absolute error was 0.0135. The mean squared error of the testing set was 0.0016 and its mean absolute error was 0.0178. As the maximum value of the target test set was 1.0, this result gives a relative error for the testing set of only 1.78%. Further details of this experiment to detect the incipient slipping can be found in [15], [16].

The simulations of the whole control model showed a performance to lift planar objects with a force ratio between 10%-30% higher than the slip ratio.

V. DISCUSSION AND CONCLUSIONS

In this paper, a tactile control model for lifting unfamiliar objects with grasp stability and human-like behavior was presented. Detailed algorithms for each one of the phases of a lifting task were designed. In the model, simulated tactile afferent responses, drive the force adjustments, and signal the detection of important events in the different phases of the lifting task. The proposed model and algorithms are strongly inspired by the current knowledge of the neurophysiology of human dexterous manipulation. Grasp stability, i.e., the prevention of accidental slips as well as of excessive fingertip forces, is a crucial property of human dexterous manipulation and is currently an open and central problem in the field of dexterous robotic manipulation of unknown objects. The model showed a good performance lifting planar objects with grasp stability.

In humans, the estimation of the friction coefficient and the detection of the incipient slipping, play a key role in the grasp stability mechanism, and are crucial components of the presented control model. Finite element analysis was used to simulate two 3-D fingers and planar objects with different friction coefficients. Artificial neural networks were used to estimate the friction coefficient and to detect the incipient slipping, using as input simulated human tactile afferent responses. The friction coefficient and the intensity of the incipient slipping were estimated with good precision. The results of the simulations show that even with a small number of tactile sensors, a good estimation of the above crucial components could be achieved.

REFERENCES