Admittance neuro-control of a lifting device to reduce human effort

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Abstract

In this paper, two admittance based control schemes for a power assisted lifting device are presented. This device can be used to hoist a heavy object interactively for reducing the operator’s burden. The proposed system integrates an admittance controller with an inner control loop that regulates the velocity of the object. The admittance is the outer loop that establishes the desired relation between the applied force to the object and its velocity. For the adaptation to a variety of loads, an online learning controller is implemented based on a neural network with backpropagation training. The overfitting of the neural network is resolved with weight decay to decrease the oscillations around the equilibrium point. Alternatively, a gain scheduling PID controller is designed for the inner loop, which measures the object weight and tunes the gains with predefined rules. The performance of these two adaptation methods is demonstrated on an experimental setup and the results illustrate that better generalization can be achieved with the neural network.

Keywords: power assist, admittance, neurocontrol, PID

1. INTRODUCTION

The power assist systems have a wide range of applications in industry and healthcare e.g. in the manipulation of heavy parts in assembly lines, in rehabilitation through physiotherapy etc. They can be used to facilitate the manipulation of heavy objects by a human operator with a considerable reduction of the required force.

The last decades many researchers have worked on power assist systems. Lee et al. [1] developed a power assisted mobile robot arm based on impedance control, introduced by Hogan [2], that follows the operator’s motion and attenuates the load force. The same control method was also used on a mobile robot arm to assist a human operator to carry a long object [3]. Further research on power assist systems was carried out for a bridge crane [4], where the velocity of the object in the vertical direction is adjusted in proportion to the applied force based on $H_{\infty}$ and $H_2$ robust control. Doi et al. [5] integrated a power assist system in the vertical direction of a pneumatic crane using a PD controller. Osamura et al. [6] implemented
a power assist system using an ideal plant model and a PD controller on a horizontal slide door to provide comfortable operational feeling.

Considering latest research [7], [8] and reviews [9] on physical human robot interaction, the control scheme that is mostly used is impedance. Ott et al. [10] made a distinction between impedance and admittance control and according to the causality of the controller, when the plant (e.g. a manipulator) performs as an admittance, then the controller is considered as an impedance and conversely. In general, impedance control has stable performance in interaction with stiff environments but suffers from inaccuracy in free-space motion due to friction and other unmodeled parameters. On the other hand, admittance control has very good accuracy in free-space motion but it depends highly on that of the inner position/velocity control loop and leads to instability when it interacts with high stiffness environments. Neural networks have been used for direct force control [11] or combined with impedance control to improve the controller robustness [12]. They have also been used for motion control of robotic manipulators [13] because they can be trained to approach the mathematical model of the structure.

The majority of the systems mentioned above, estimate the assisting force according to the applied force by the user, utilizing a sensor that is mounted between the load and a handle [1], [6]–[8]. This is a pretty straightforward technique with many advantages because the operator guides the object through the handle but it lacks the flexibility and intuitiveness of direct handling of the object. Another approach that withdraws the need of a handle would be the mounting of the loadcell within the suspension system to facilitate the direct handling of the object by the operator [3], [4].

In this paper, a single degree-of-freedom power assist system is developed that can be used for moving objects in the vertical direction. An admittance controller is implemented to establish a relationship between the imposed forces and the motion of the object, combined with a neural network (NN) with online training that acts as a velocity controller and is able to adapt to the variable plant parameters. The proposed control scheme does not require a model of the system, unlike most of the systems mentioned above. The training of the NN is adjusted to avoid overfitting and to eliminate the remaining oscillations. For comparison, a gain scheduling PID is implemented for the velocity control instead of the neural network controller. A set of objects with different weights are lifted/lowered on an experimental setup with direct manipulation of the object, without the need of a handle for higher flexibility, and the performance of the designed controllers is investigated.

2. THE POWER ASSIST SYSTEM

As it is illustrated in fig. 1, the developed system consists of an electric motor that is mechanically coupled with a drum. Rotation of the motor shaft wraps a wire rope around the drum, moving the object that is attached to the free end along the vertical direction. Fig. 1-a presents a schematic representation of the power assist system while fig. 1-b the experimental setup.

The position of the object is measured from a rotary encoder installed at the drum shaft and the velocity of the object \( V \) is calculated by numeric differentiation. For the force measurement, a loadcell is mounted between the rope and the suspended object and the operator manipulates the object itself rather than by
using a handle. As a result, the operator could manipulate the object in a more physical and intuitive manner. The measured force consists of three main components; the weight of the object \((mg)\), the human force \((Fh)\) and the inertial forces \((m\dot{V})\). We assume that the wire rope is always tensed and that its spring constant is very high. The masses of the loadcell and the suspension system that act below the force sensor are assumed to be part of the load, while the rest that act above the sensor are compensated by the control system as it is described in chapter 3.2.

![Diagram](image.png)

Figure 1: The power assisting device: (a) schematic representation, (b) experimental setup.

2.1. System analysis

Before the design of the controller, a brief analysis of the system is conducted. A single degree of freedom system is assumed, where a mass interacts with the environment as it is shown in fig. 2. The mass of the object and its velocity are \(m\) and \(V\), respectively, and the actuator force and external measured force are \(F\) and \(F_s\). The weight \(mg\) of the object is measured and is compensated by the static friction \(T\) that appears in the drive system. The large value of \(T\) is achieved with a high transmission ratio and \(mg<T\), otherwise if \(mg>T\), a breaking system is required. The walls of the guide that are illustrated in fig. 2 are not parts of the actual plant but are added to model the static friction appeared in the drive system. The motion of the mass can be expressed by the following equation:

\[
m\ddot{V}=F+F_s+mg-T
\]  

(1)

In section 3.1, it is demonstrated that the effects of friction forces are compensated by the control system. The known component of gravitational force \(mg\) can be numerically removed from the measured force and the \(F_s\), which is the force measured by the sensor can be given by:

\[
F_s=F_h-m\dot{V}
\]  

(2)

To obtain an accurate measurement of the human force \(F_h\) from the sensor signal, the term \(m\dot{V}\) should be as small as possible \((m\dot{V} \ll F_h)\), otherwise it could affect the dynamic response and this phenomenon is the main disadvantage of using indirect force measurement.
3. DESIGN OF THE CONTROLLER

In the proposed scheme, an admittance controller is integrated along with a velocity controller. The admittance controller, that is used to facilitate the interaction, receives the measured force \( F_s \) and outputs the velocity \( V \). The velocity controller increases the system robustness in the absence of accurate model and its flexibility since it can operate with a range of object weights.

3.1. Admittance Controller

To achieve power assisting movement, a desired relationship between the input force and the output velocity should be established. Both impedance and admittance control have the ability to establish such a relationship. In common implementations of impedance control, the external force \( F_s \) is measured and \( F \) is commanded such that the following equation of the motion is enforced:

\[
F_{\text{d}}\ddot{V} + c_d\dot{V} = F_s
\]  

(3)

This is a typical linear second-order relationship, where \( \dot{V} = V_{\text{d}} - V_r \) is the deviation from a reference velocity \( V_r(t) \). The parameters \( m_d, c_d \) represent the desired inertia and damping respectively. It should be ensured that when \( F_h = 0 \), the actuating force \( F \) will be zero too and the object will remain still. This is achieved by removing the frequently used stiffness term \( k_d \) in eq. (3) that would produce a restoring force, when there is a deviation from a reference position.

By comparing eq. (1) with the desired behaviour in eq. (3), the typical impedance control law can be derived which gives the force applied by the actuator \( F \). Authors in [10] mentioned that the implementation of this controller requires information about the force/torque applied by the actuator and to achieve good accuracy, a sufficient model of the plant should be available. In the current work, we do not have information about the actuator’s applied torque and the operation of the system under a variety of loads would make the identification of the plant parameters, and particularly that of friction, very time consuming.

As an alternative, admittance control is considered because it accepts force inputs and yields motion outputs and implements an automatic control system that imposes the actuating force \( F \) indirectly to the plant through a velocity control loop. This procedure fits better to power assist systems, where there is no contact with stiff environment and the tasks are performed with free-space motion. Since the accuracy of admittance control depends highly on that of the velocity control system, a sufficient model of the plant...
should also be available. In the proposed scheme the model of the system is not necessary because a NN controller is integrated in the inner velocity loop.

In the block diagram of fig. 3-a, the proposed controller is illustrated, where the external loop accommodates the admittance controller and in the inner loop the velocity controller is implemented by the online trained NN. Figure 3-b shows an alternative control system, where the NN controller is replaced by a gain scheduling PID. The main control loop is described by eq. (3), where the reference velocity $V_r$ is set equal to zero as a necessary condition for the object to remain still, when the force measured by the loadcell is zero ($F_s=0$). By tuning the parameters $m_d$ and $c_d$ we can define the acceleration and velocity of the object respectively given a value $F_s$. When $V_r = 0$, then $\dot{V} = V_d$ and the admittance control law can be rewritten as follows:

$$m_d \dot{V}_d + c_d V_d = F_s$$  \hspace{1cm} (4)

The transformation of Eq. (4) in the discrete time domain using a sampling period $T_s$ and expressed in terms of $V_d$, describes the admittance control law that is used for the experimental implementation:

$$V_d[kT_s] = \frac{1}{m_dT_s + c_d} \left( T_s F_s[kT_s] + m_d V_d[kT_s-T_s] \right)$$  \hspace{1cm} (5)

3.2. Velocity Controller

An internal loop of velocity control accepts the desired velocity from the output $V_d$ of the admittance, as it is shown in figures 3-a and 3-b. By measuring the velocity $V$ of the motor with an encoder from a feedback loop, the error $V_e$ between the desired $V_d$ and actual velocity $V$ derives. The velocity controller outputs the appropriate voltage $u$ to drive the motor and as a result, the desired actuating force $F$ is applied to the plant carrying out the impedance function. In that way, by applying a force $F_h$ to the suspended object, the admittance controller will produce a desired velocity $V_d$ and the speed controller will regulate the velocity of the motor to achieve a lowering/hoisting of the object.

The main parameters that influence the plant dynamics are the actuator’s dynamics and the mass $m$ of the object. Since the designed system should perform under a variety of loads and present robustness in disturbances, two adaptive velocity controllers are designed.
Neural Network Controller. A feedforward neural network velocity controller is implemented, as shown in fig. 3-a. The NN is composed by three layers with the configuration (2-6-1), i.e. two linear neurons (L) in the input layer, six in the hidden and one in the output respectively as it is illustrated in fig. 4. A sigmoid function (S), bounded between -1 and 1, is used for the neurons in the hidden and output layers. The well-known backpropagation [14] training algorithm is used for the online adaptation of the network’s weights $w$ and thresholds $b$, which are initiated randomly. This supervised learning approach is used for temporal learning [15], which is usually followed in control problems. Therefore, there have not been used pairs of training data, as in the case of structural learning, but only the error signals for adapting the weights online.

The velocity error $V_e$ ($V_e = V_d - V$) is used in the backpropagation part and is also fed back to the input of the NN together with the previous one $[kT-T]$ in order to close the controller’s loop. This type of controller will approximate the inverse dynamics of the overall system and will drive the motor accordingly until the actual velocity ($V$) of the plant reaches the desired value ($V_d$) and the network will be considered trained.

Since the training of the NN is essential for the operation of the controller, it is active throughout the operation and eventually could lead to its overfitting [16]. This occurs when too much information is transmitted through the network and after a certain amount of time the network does not improve its ability to capture the underlying function because the response of the controller has become too complex. Overfitting could have undesired effects in high accuracy applications and particularly in a lifting device, by causing oscillations.
One method to constrain the training process and avoid overfitting is called weight decay [17]. This method allows connection weights to exponentially decay towards zero at a rate proportional to their magnitude, in accordance with the temporal learning approach described above. To verify that the weight decay method eliminates the oscillatory effects, it is implemented in the experimental setup according to the rule:

$$\Delta w_{ij}(n + 1) = bp_{ij}(n) - \lambda w_{ij}(n)$$  \hspace{1cm} (6)

Where $\Delta w_{ij}(n + 1)$ is the new value that is added to the weight, $bp_{ij}(n)$ the value for training that derived from the backpropagation algorithm and $\lambda$ is the decay factor (between 0 and 1). After trial and error the factor $\lambda$ was selected equal to 0.1 for the input neurons on the hidden layer and 0.8 for the output neurons of the hidden layer. In fig. 5-a, the velocity waveform of an object is plotted that is manipulated by a human operator using the proposed admittance and NN controller with simple backpropagation training. At the end of manipulation the object does not immobilize, as it was supposed to, but it oscillates around the equilibrium point. As it is illustrated in fig. 5-b, any remaining oscillations are diminished no matter how long the process is running, by implementing the weight decay training. Furthermore, with weight decay the velocity of the object during manipulations demonstrates smoother transient state without deteriorating the overall performance of the system.

![Velocity waveform](image)

**Figure 5:** Manipulation of an object with $m=2$kg by a human operator. At the end of manipulation remaining oscillations due to overfitting are illustrated (a) without and (b) with weight decay training.

**PID Gain Scheduling.** The second velocity controller is a gain scheduling PID as shown in figure 3-b. We selected this type of controller because it is a classic controller, relatively easy to implement and has adaptation capabilities. To determine the gains of the controller we used the heuristic method of Ziegler-
Nichols with “no overshoot” rules for a pair of different weights (1kg & 3kg). The adaptation of the gains to the suspended weight takes place offline at the beginning of the process during the initialization, where the object is weighted from the loadcell and the gains are computed with linear interpolation. To investigate the ability of the interpolation to construct acceptable gain values, we calculate the gains for an intermediate weight (2kg) experimentally with Ziegler-Nichols and compare them with the results from interpolation. As it is shown in table 1, the gains of the PID from the two methods have very close values and as a result, this method can produce valid gains. More sample weights could be used or greater range between them if our experimental setup had bigger payload.

| Table 1. Gains of the PID controller from Ziegler-Nichols and linear interpolation |
|-----------------|-----|-----|-----|
|                 | $K_P$ | $K_I$ | $K_D$ |
| For $m=2kg$ with Ziegler-Nichols | 400 | 2777 | 38.4 |
| For $m=2kg$ with linear interpolation | 405 | 2793 | 39.15 |

4. EXPERIMENTAL EVALUATION

4.1. Setup

Our experimental setup consists of a DC motor with high ratio gearbox for non-backdrivability along with a custom-made hoist, as shown in fig. 1-b. The maximum lifting/lowering velocity is 60mm/s and the payload is 6kg. The rotational speed of the motor is controlled with pulse width modulation (PWM) method through a motor driver and is expressed as a percentage of the rated rotational speed. Both the motor and the sensors are connected to a personal computer with Phidget interfaces. The communication between the computer and the external interfaces is performed via universal serial bus (USB) with sampling period $T_s=8ms$.

In order to switch to power assisted motion, an initialization process must take place at the beginning. The object weight is measured at equilibrium point and is removed from the input signal to compensate the gravity. In addition, the appropriate gains are calculated for the gain scheduling PID controller.

To implement the admittance controller, the following parameters are selected heuristically:

$$m_d = 1kg, \quad c_d = 15 \frac{Ns}{m}$$

The mass $m_d$ indicates the desired mass for our power assisted system. This value refers to the desired behaviour of the system that should be accomplished regardless of the actual object weight. The parameter $c_d$ represents the viscous damping in which the desired mass moves and indicates the sensitivity of our system to external forces. A desired damping factor of 15Ns/m indicates that in order to move an object with speed 0.06m/s (rated speed), the required force is:

$$15 \frac{Ns}{m} * 0.06 \frac{m}{s} = 0.9 N$$

To verify this assumption three different objects weighting 1kg, 2kg and 3kg are selected and a constant force equal to 0.9N is applied to them in both directions, by adding and removing a mass equal to 0.09kg.
Then, the velocity of the object in each experiment is plotted and the results are used to investigate the performance between the two controllers in the transient and the steady states. It is expected that the object should move with a speed equal to 0.06m/s.

4.2. Neural Network Controller

To begin with, the NN controller with weight decay is implemented in digital form along with the admittance controller (Eq. 5).

For three different masses a constant force equal to 0.9N is applied for approximately two seconds in each direction causing the lowering (negative values of velocity) and the hoisting (positive values of velocity) of the object respectively, as in fig. 6-a. The experiments are conducted under a constant force because we want to investigate the performance of the controllers under the same conditions. Using a mass to generate that force, we can also investigate the robustness of the controller in changes of the dynamic characteristics. The criteria for the evaluation of the control methods are the quality of the response rate, the response smoothness and the overshoot.

In figure 6-b, a summarized graphical representation of the experiments is presented using the neural network controller. The system response is very fast in both directions, specifically in the acceleration of the load. When the external force is removed, the load stops very quickly as expected. Another notable remark is that the velocity in both directions differs from the rated one and between the different weights mainly because of the existence of the gravitational component as an external torque to the motor. The ripples exist only during the steady state and are attributed to residual vibrations due to the flexibility of the system structure.

4.3. PID Gain Scheduling Controller

After substituting the NN with the PID gain scheduling controller, the same series of experiments are conducted. The gains of the controller are calculated in the system initialization, with the Ziegler-Nichols tuning for the objects of 1kg and 3kg and with linear interpolation for the rest. For the integral term an anti-windup tracking is added to avoid excessive overshooting due to the saturation of the output velocity. As it is illustrated in figure 6-c, the PID gain scheduling controller demonstrates worse uniformity of the velocity among the different weights and especially during the transient state. The responses at the acceleration are similar with those of the NN controller but during deceleration, leaps on the velocity appear. During the steady state, the deviation of the average velocity from the expected one appears for the same reason as in the neural network, due to the gravitational component. The ripples are slightly more visible and occur both in transient and steady state.
Figure 6: (a) The actual and ideal external force profile that was used in the experiments and the velocity of the object for lowering and lifting with (b) NN control and (c) with PID gain scheduling control.

4.4. PID vs. Neural Network

Before we come to a conclusion, the two velocity controllers are compared for each of the loads of the previous experiment. The velocity graphs of the NN controller and the PID gain scheduling are overlaid in figures 7a - 7c.

Starting from the object with mass $m=1kg$, we can see in figure 7-a that both controllers accelerate to steady state at the same time. The PID controller causes much less ripple than the NN and stays closer to
target velocity, but it needs longer time for the object to stop after the lifting. In figure 7-b, with m=2kg we can also derive valuable information for the performance of the PID with gains that resulted from interpolation. The rising time of both controllers is almost the same, but the PID causes small leaps of the velocity during deceleration and also causes more ripples than the NN. For the heaviest object of our experiment with m=3kg we can clearly see in fig. 7-c that the NN outperforms the PID. The latter causes even higher leaps during deceleration and more intense ripples, while the NN responds very fast and with very little oscillation of the velocity.

![Figure 7: Velocity of an object m=1kg (a), m=2kg (b) and m=3kg (c) for lowering and lifting with PID and NN](image-url)
Summarizing the results, even though the scheduling PID controller has similar performance with the NN in small loads, it causes undesirable effects in greater loads. On the other hand, the performance of the NN is not affected by the increase of the load and has higher robustness in rejecting disturbances. It can be concluded that the NN as a velocity controller has better generalization than the PID gain scheduling and should be preferred in power assist systems, where heavy objects are carried.

4.5. Manipulation by Human

In this section, the performance of the controllers in the manipulation of an object by a human operator is presented. The purpose of these experiments is to demonstrate the power assist system under real conditions including the human factor. The difference from the previous experiments is that the operator cannot apply constant force, but a variable one that changes intuitively as the operator observes the velocity of the object.

A medium weight equal to 2kg is selected and a force is applied in order to lower it in a certain distance (0.1m) and then hoist it at the initial position. For the admittance controller the same parameters are used \( m_d = 1kg, \ c_d = 15Ns/m \). According to these values, a force \( F_h = 0.9N \) should be applied to the object to reach the maximum speed. The actual force \( F_h \) applied by the operator and the corresponding velocity \( V \) response are studied in order to investigate the performance of the proposed synthesis of the admittance and velocity controllers.

In figure 8-a, the external force with the PID gain scheduling controller is presented. It is shown that the force \( F_h \) is quite higher than the expected mainly because the operator takes into account the dynamics of the actual mass. Very quickly, the operator learns the dynamics of the power assisted system and adjusts it. This explanation is demonstrated better by the variation of the force in figure 9-a, where the NN controller is implemented. The ripples of the external force at the end of each movement are caused from remaining oscillations of the object and are being rejected by the admittance controller. The noise of the input force signal is also rejected and as a result it is shown that the admittance controller also acts as a low pass filter.

The result of the applied force is the velocity of the object that is illustrated in figures 8-b and 9-b for PID and the NN respectively. These results are similar to those shown in figure 7-b and we can see that both controllers respond very fast with the neural network having slightly better performance during the transient state. The rippling effect is less evident in the PID gain scheduling and is unnoticeable during operation for both controllers.
Figure 8: PID gain scheduling for lowering and lifting: (a) applied force by the operator, (b) velocity of object

Figure 9: NN for lowering and lifting: (a) applied force by the operator, (b) velocity of object
5. CONCLUSION

In this study, a control method for a power assisting lifting device was developed by integrating an admittance controller and a neural network with online training. The experiments that were conducted proved that the admittance controller established the desired relationship between the force applied by a human operator and the velocity of the object and the NN, as a velocity regulator, could successfully adapt to the absence of a system model. The problem of the NN overfitting that caused oscillation was solved using weight decay along with the standard backpropagation training.

In addition to the neural network, a gain scheduling PID was implemented for comparison purposes. Both of the velocity regulators managed to attain the velocity provided by the admittance controller although they did not have knowledge of the plant dynamics. In the effort to adapt to the different object weights, the NN controller proved to be more appropriate, specifically in higher loads. The online training of the NN could also adapt better to disturbances in contrast with the PID gain scheduling that tuned its gains only at the beginning of the process. On the manipulation of the object by a human operator, our system performed the motion very well and our power assisted design was verified.

The proposed control method could have potential use in assembly operations of heavy objects, where fine precision is required. With further elaboration of the current study, the proposed scheme could be implemented for human-robot co-manipulation of objects.

6. REFERENCES


