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Control of a Power Assisted Lifting Device

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Abstract. In this paper, two control schemes for a power assisted lifting device are presented. Such a device can be used to hoist a heavy object in cooperation with a human by reducing the operator's burden. The proposed system includes an admittance controller that establishes the desired dynamic relationship between the applied force to the object and the motion, while an inner control loop regulates the velocity of the object. For the adaptation to a variety of loads, an online adaption controller is implemented based on a neural network with backpropagation training. Alternatively, a gain scheduling PID controller is designed for the inner loop. This controller 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 are illustrated and discussed at the end of this manuscript.

Keywords. Power Assist, Admittance Control, Neural Network Control, PID Gain Scheduling

1. Introduction

A power assist system can be used to facilitate the manipulation of a heavy object by a human operator with a considerable reduction of the required force. This system has 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.

The last five decades many researchers have worked on power assist systems. Lee (Lee et al., 1999) developed a power assisted mobile robot arm, based on impedance control (Hogan, 1985), 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 (Hayashibara et al., 1999). Later, a hybrid control framework was proposed that unifies impedance and admittance control (Ott et al., 2010). According to Ott, the mapping of force inputs to motion outputs provides very good performance when the environment is soft but results in poor accuracy when the environment is stiff.

Further research on power assist systems was made on a bridge crane (Miyoshi & Terashima, 2004) that controls the velocity of the object in the vertical direction in proportion to the applied force based on H_∞ and H_2 robust control. Doi installed a power assist system in the vertical direction of a pneumatic powered crane using a PD controller (Doi et al., 2008). Osamura implemented a power assist system with an ideal plant model and a PD controller on a horizontal slide door to provide comfortable operational feeling (Osamura et al., 2007).

For force control problems, neural networks have been widely used (Lin & Tzeng, 1999). Alternatively, the neural network technique has been combined with impedance control as an addition in order to improve the controller robustness (Jung & Hsia, 1998).

The majority of the systems mentioned above, calculate the assisting force according to the applied force by the user. The force is either received from the manipulation of the force sensor, which is a pretty straightforward technique with many advantages, or indirectly from the manipulation of the object itself. The latter incorporates a loadcell within the suspension system that withdraws the need of a handle and facilitates the intuitive handling of an object by the operator.

In this paper, a single degree-of-freedom power assist system is developed that can be used for moving objects in the vertical direction. Admittance control is implemented to establish a relationship between the imposed forces and the motion of the object. To ensure that our object reaches the desired velocity that derived from the admittance controller, a neural network controller with online training is designed that adapts to the variable plant parameters, unlike most of the systems mentioned above, which perform under certain parameters or boundaries. A gain scheduling PID was also implemented for the velocity control instead of the neural network controller. A set of objects with different weights were used on an experimental setup to investigate the performance of the designed controllers in hoisting/lowering and adaptation.

2. System Description

The proposed system (see Fig. 1) consists of an electric motor that is mechanically coupled with a drum. Rotation of the motor shaft causes a wire rope to wrap around the drum and move the object that is attached to the edge along the vertical direction.

The position of the object is calculated from a rotary encoder installed at the drum shaft. Using a numeric differentiation, the velocity of the object (V) is calculated. For the force measurement we selected to mount a loadcell between the rope and the suspended object and let the operator manipulate the object itself rather than use a handle. As a result, the operator would manipulate the object in a more physical manner. The measured force consists of three main components; the weight of the object (mg), the human force (F_h) 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 mass of the loadcell is very small and it has no significant effect on the system dynamic response.

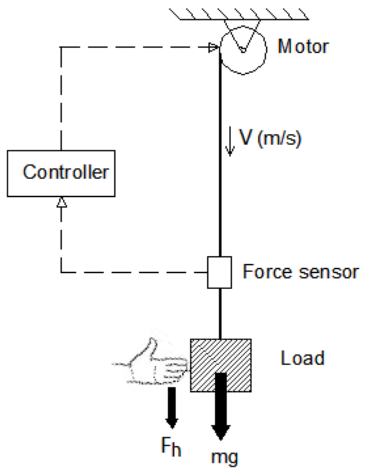

Fig. 1. Layout of control system

3. Design of the Controller

For the controller design let's assume a simplified single degree of freedom system in which a mass interacts with the environment (see Fig. 2). The mass of the object and displacement are m and x, respectively, and the actuator force and external measured force are F and F_{ext}. The weight mg of the object is considered known and is compensated[1] by the static friction T that appears in the drive system. The walls of the guide that are illustrated in Fig. 2 are not parts of the actual plant but were designed in order to model the static friction in the drive system. The motion of the mass can be expressed by the following equation:

$$m\ddot{x}=F+F_{ext}+mg-T \tag{1}$$

Later it will be demonstrated that the effects of friction forces can be neglected. The known component of gravitational force mg can be numerically removed from the measured force and the F_{ext} can be given by the equation:

$$F_{ext}=F_h-m\dot{V} \tag{2}$$

In order to obtain an accurate measurement of the human force F_h, the term $m\dot{V}$ should be as small as possible $(m\dot{V} \ll F_h)$, otherwise it could affect the dynamic response.

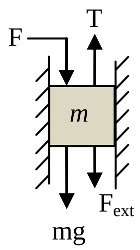

Fig. 2. Single degree-of-freedom model

3.1. Admittance Control

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_{ext} is measured and F is commanded such that the following equation of the motion is enforced:

$$m_d\ddot{\tilde{x}}+c_d\dot{\tilde{x}}+k_d\tilde{x}=F_{ext} \tag{3}$$

This is a typical linear second-order relationship where $\tilde{x}=(x_d-x_r)$ is the deviation from a reference trajectory $x_r(t)$. The parameters m_d, c_d and k_d represent the desired inertia, damping and stiffness respectively. In our system we do not want to include a restoring force so we set $k_d=0$, in order to ensure that the actuator force F will be zero when the user does not apply F_{ext}. By setting $\dot{\tilde{x}}=\tilde{V}$ and $k_d=0$ in (3), we get:

[1] This assumption is valid only when $mg \le T$. A large static friction T can be achieved with a high transmission ratio. In different case when $mg > T$, a breaking system is required.

$$m_d\dot{\tilde{V}}+c_d\tilde{V}=F_{ext} \tag{4}$$

where $\tilde{V} = V_d - V_r$.
By comparing Eq. (1) with the desired behaviour in Eq. (4), we can derive the impedance control law which gives the force applied by the actuator F. This method will not be used, since it requires a very good estimation of the plant parameters. In our system, it is quite time consuming to calculate the dynamics because these are changing, by lifting a variety of objects.

As an alternative, admittance control is considered. In contrast with the impedance control, admittance control accepts force inputs and yields motion outputs and implements an automatic control system that imposes the actuating force F indirectly to the plant. This procedure fits better to power assist systems. Admittance control also provides high level of accuracy in non-contact tasks.

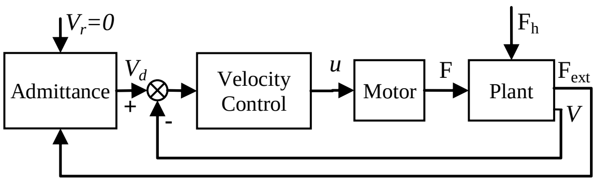

Fig. 3. Block diagram of control system

In the block diagram of Fig. 3, the control system is illustrated. It consists of the main control loop for the admittance control and an inner loop for the velocity controller. The main control loop is described by Eq. (4). The reference velocity V_r is set to zero as a necessary condition for the object to remain still when no F_{ext} is applied. When $V_r = 0$, then $\tilde{V} = V_d$ and the admittance control law can be rewritten as follows:

$$m_d\dot{V}_d+c_dV_d=F_{ext} \tag{5}$$

The transformation of Eq. (5) 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:

$$V_d[kT_s]=\frac{1}{m_d+T_sc_d}\left(T_sF_{ext}[kT_s]+m_dV_d[kT_s\text{-}T_s]\right) \tag{6}$$

3.2. Velocity Controller

In series with the admittance controller a velocity controller is placed, as shown is Fig. 3. The velocity controller inputs the error V_e between the desired velocity V_d that derived from the admittance controller and the measured velocity V from a feedback loop and outputs a voltage u to drive the motor. As a result, the actuating force F is derived indirectly from the velocity controller and any unmodeled parameters are treated as disturbances and are diminished.

The mass m of the object is a parameter that has great impact in the plant dynamics and cannot be considered as a disturbance. Since we want our system to perform under a variety of loads an adaptive controller must be designed.

Neural Network Controller. Since the system dynamics depend on the object weight, a Feedforward Neural Network (FNN) velocity controller is implemented, as shown in Fig. 4. The FNN is composed of 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 (see Fig. 5). A sigmoid function (S), which is bounded in magnitude between -1 and 1, is used for the neurons in the hidden and output layers. The well-known backpropagation (Wasserman, 1989) training algorithm is used for the online adaptation of the network's weights and thresholds b, which are set randomly in the beginning.
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 FNN together with the previous one [kT-T] in order to close the controller's loop.

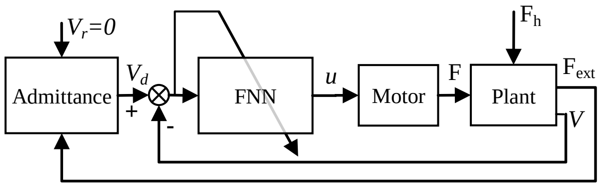

Fig. 4. Block diagram with neural network velocity control

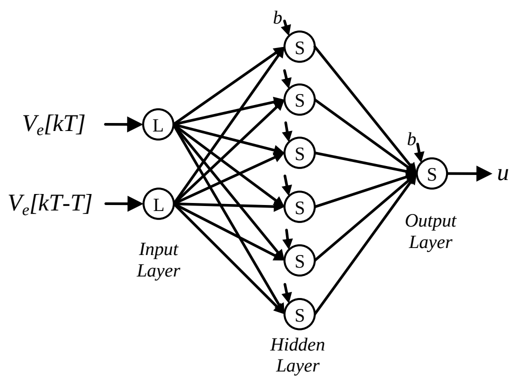

Fig. 5. Neural network configuration

PID Gain Scheduling. The second velocity controller is a gain scheduling PID (see Fig. 6). The gains of the controller are calculated for a pair of different weights (1kg & 3kg) according to the Ziegler-Nichols method with "no overshoot" rules. More sample weights could be used or greater deviation between them if our experimental setup had bigger payload. This method includes offline adaptation by computing the gains with linear interpolation at the beginning of the process during the initialization.

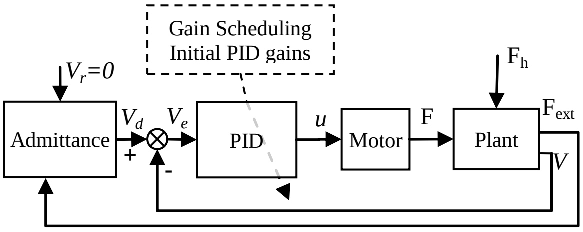

Fig. 6. Block diagram with gain scheduled PID velocity control

4. Experimental Evaluation

4.1. Setup

Our experimental setup (see Fig. 7) consists of a DC motor with high ratio gearbox for non-backdrivability along with a self-made hoist. The maximum lifting/lowering velocity is 0.06m/s and the capacity 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. The mass of the loadcell is equal to 0.15kg and does not influence the dynamic response of the system.

Both the motor and the sensors are connected to a personal computer with Phidget interfaces. The computer is a common laptop with 2.1GHz CPU clock that acts as a controller. The communication between the computer and the external interfaces is performed via universal serial bus (USB) with sampling period T_s=8ms.

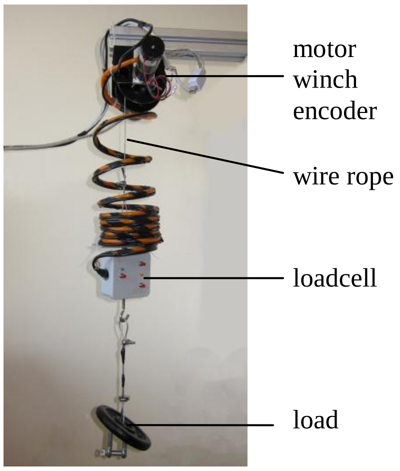

Fig. 7. Experimental setup

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 in the gain scheduling PID controller.

To implement the admittance controller the following parameters are used:

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

The mass m_d indicates the desired mass for our power assisted system. This value refers to the desired behaviour of the system and 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. Assuming $c_d = 0$, a small external stimulation would cause the object to move indefinitely because no frictional forces are modelled. The actual frictional forces on the plant would be perceived as disturbance and would be compensated by the velocity control system. 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:

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

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. PID Gain Scheduling

To begin with, the PID is implemented in digital form along with the admittance controller (Eq. (6)). The gains of the controller are calculated in the system initialization. For the integral term an anti-windup tracking is added to avoid instability due to the saturation of the output velocity.

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 (see Fig. 8). The experiments are conducted under a constant force because we want to investigate the performance of the controllers under the same conditions. The gains for the mass of 2kg resulted from interpolation, while the other two objects coincide with the gain values obtained by the Ziegler-Nichols tuning. The criteria for the evaluation of the control methods are the quality of the response rate, the response smoothness and the overshooting.

In Fig. 9, a summarized graphical representation of the experiments is presented. The system response is very fast in both directions, specifically in the acceleration of the load. During deceleration (when the external force is removed) a small delay appears which becomes more evident with the increase of the load. 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 are attributed to residual vibrations due to the flexibility of the system structure.

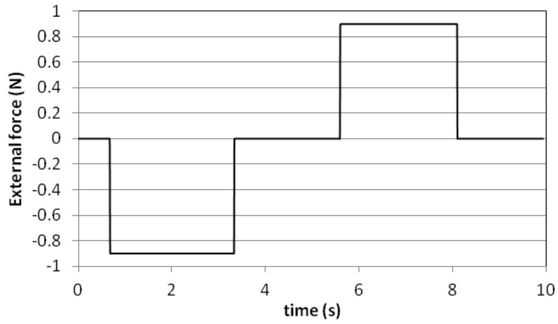

Fig. 8. External force profile that was used in the experiments

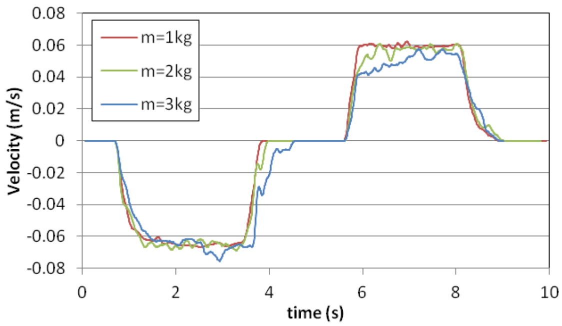

Fig. 9. Velocity of object for lowering and lifting with gain scheduling PID control

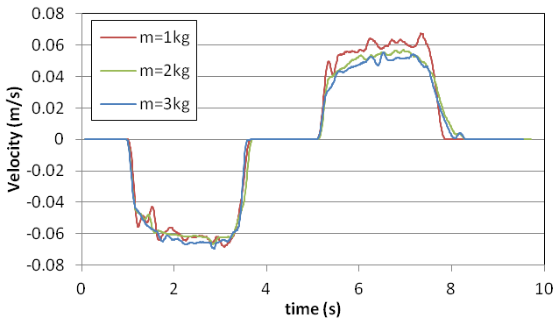

Fig. 10. Velocity of object for lowering and lifting with neural network control

4.3. Neural Network Controller

Substituting the PID controller with the neural network, the same series of experiments are conducted. In this case, the weights and thresholds of the neural network are adapted online.

As it is illustrated in Fig. 10, the neural network as a velocity controller demonstrates better uniformity of the velocity among the different weights and especially during the transient state. The responses at the acceleration and deceleration of the object are very similar and meet the desired specifications. During the steady state, the deviation of the average velocity from the expected one appears for the same reason as in the PID scheduling, due to the gravitational component. The ripples are considerably less and occur only during the steady state.

4.4. PID vs. Neural Network

Before we come to a conclusion a comparison between the two velocity controllers should be made. Therefore, for each load of the experiments demonstrated in Fig. 9 and 10, the velocity graphs of the gain scheduled PID and the neural network are overlaid in three figures.

Starting from the object with mass m=1kg, we can see in Fig. 11 that both controllers accelerate in steady state at the same time. The PID controller causes much less ripple than the neural network and more steady velocity, but it needs longer time for the object to stop after the lifting.

In Fig. 12, comparative results for the object of m=2kg are demonstrated. In this case we can also derive valuable information for the performance of the PID with gains that resulted from interpolation. Both controllers respond very fast, while the PID causes small leaps of the velocity during deceleration. Unlike the previous graph, appeared in Fig. 11, here the PID controller also causes more ripples than the neural network.

For the heaviest object of our experiment with m=3kg we can clearly see (Fig. 13) that the neural network outperforms the PID gain scheduling. The latter causes even bigger leaps during deceleration and more intense ripples, while the neural network responses very fast and with very little oscillation of the velocity.

Summarizing the results, the scheduling PID controller even though it performs better in small loads, it causes undesirable effects in greater loads. On the other hand, the performance of the neural network controller is not affected by the increase of the load and has better adaptability in rejecting disturbances. It can be concluded that the neural network 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.

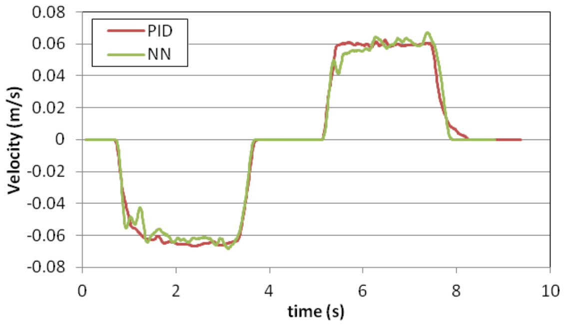

Fig. 11. Velocity of object (m=1kg) for lowering and lifting with PID gain scheduling and NN

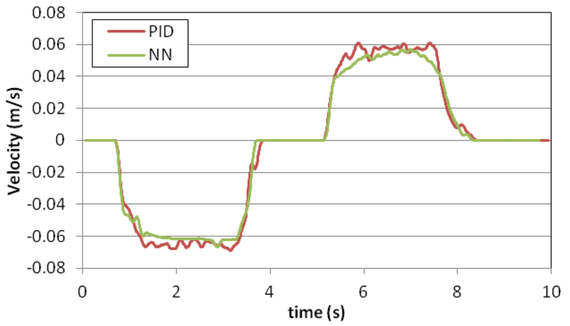

Fig. 12. Velocity of object (m=2kg) for lowering and lifting with PID gain scheduling and NN

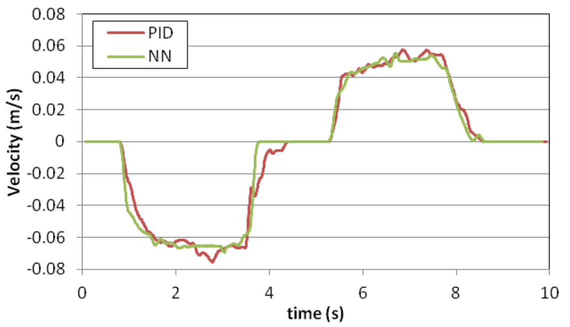

Fig. 13. Velocity of object (m=3kg) for lowering and lifting with PID gain scheduling and NN

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 differences from the previous experiments are that the system interacts with the human and that the applied force is not constant but depends on the operator.

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 ($m_d = 1kg,\ c_d = 15\,Ns/m$). According to these values, a force equal to 0.9N is required in order the object to reach the maximum speed. We want to study the actual force that is applied by the operator and the corresponding velocity response in order to investigate the performance of proposed synthesis of the admittance and the velocity controllers.

In Fig. 14, the external force with the PID gain scheduling controller is presented. The force that is applied at the beginning of the movement tends to be more than 0.9N 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 the force. This explanation is demonstrated better by the variation of the force in Fig. 16 where the neural network 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 Fig. 15 for the PID gain scheduling controller and in Fig. 17 for the neural network. These figures are similar to Fig. 12 from the previous experiments. 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.

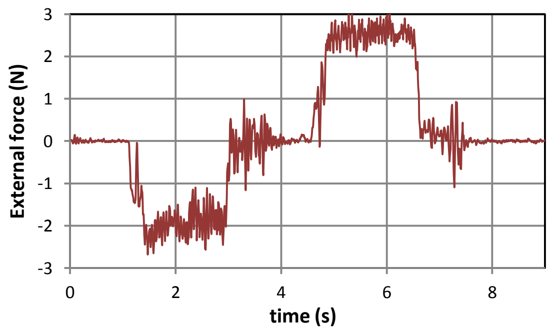

Fig. 14. Applied force by human for lowering and lifting with PID gain scheduling

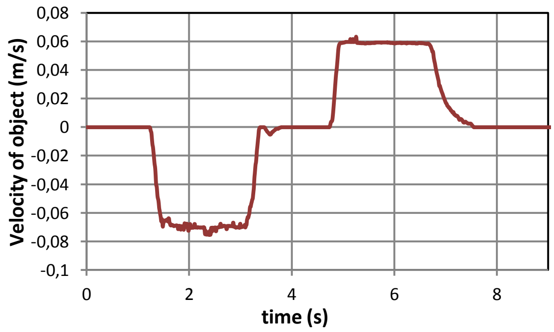

Fig. 15. Velocity of object for lowering and lifting with PID gain scheduling

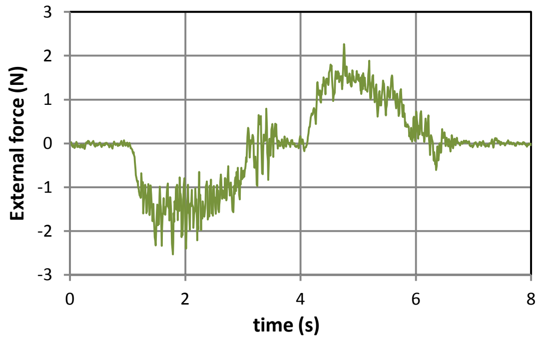

Fig. 16. Applied force by human for lowering and lifting with NN

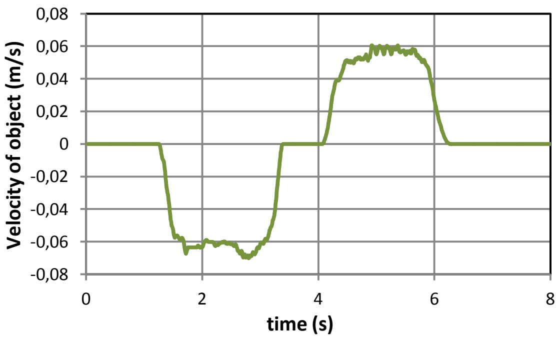

Fig. 17. Velocity of object for lowering and lifting with NN

5. Conclusion

In this paper, a control method for a power assist system was developed using admittance control in series with an inner velocity controller. The experiments that were conducted proved that the admittance controller established the desired relationship between the external forces and motions. For the velocity regulator, a gain scheduling PID and a neural network controller were implemented. Both of them 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 neural network controller proved to be more appropriate, specifically in higher loads. The online training of the neural network 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 cooperative motion very well and our power assisted design was verified. The neural network in the cooperative motion had a slightly better performance than the PID gain scheduling.

For further elaboration of the current study, the implementation of the designed controllers in a 6 degrees-of-freedom robot is planned not only in the vertical direction but in 3D space, along with the experimentation with greater loads.

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