Signal Prediction in Bilateral Teleoperation with Force-Feedback

Mateusz Saków, Krzysztof Marchelek, Arkadiusz Parus, Mirosław Pajor and Karol Miądlicki

Abstract In the paper a sensor-less and self-sensing control scheme for a bilateral teleoperation system with force-feedback based on a prediction of an input of a non-linear inverse model by prediction blocks was presented. As a part of the paper a method of a time constant estimation of the prediction block was also proposed. The prediction method of an input of an inverse model was designed to minimize the effect of the transport delay and the phase shift of sensors, actuators and mechanical objects. The solution is an alternative to complex non-linear models like NARX or artificial neural networks, which requires complex stability analysis, and control systems with high computing powers. The effectiveness of the method has been verified on the hydraulic manipulator's test stand.

Keywords Bilateral teleoperation · Non-linear inverse modeling · Signal prediction

1 Introduction

Nowadays it is hard to find a factory without a device being controlled by a joystick, a keyboard or other type of remote control [14]. From early 60's of the previous century

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research is being carried out to obtain remote control [5] or partially autonomous [31] device operation. The breakdown into remotely controlled and autonomous devices was proposed, when scientists discovered the critical value of a delay in the communication channel, which had a crucial impact on a stability of the telemanipulation system [31]. However, the transmission delay is not the only component of an aggregate delay in the teleoperation system. The aggregate delay usually consists a processing time of an analog-digital converter, a time of calculation completion by a controller, a processing time of a digital-analog converter and transition states of dynamic properties of actuators, sensors and mechanical objects [31].

The problem of a stability and a counteract of the effect of the delay in the communication channel are addressed by many scientific papers [5, 10, 29, 34, 36]. At the beginning research was focused on methods maintaining the stability which were the move-and-wait strategy and the deliberate slowdown of operator's motion when the environmental object was approached [5]. Later, sensor based control schemes was redesigned and equipped with a shared compliant control method by Kim [11]. The shared compliant control included flexible bodies in a mechanical structure of a Master manipulator. W. S. Kim also proposed a control scheme of bilateral force control, based on a position error between Master and Slave manipulators which control scheme has improved transparency of a force in the force-feedback communication channel [10]. However, none of these control schemes could guaranteed the stability of a system, when large delays are expected in the communication channel. Only, after the modification of the communication channel based on a wave variables, bilateral teleoperation systems were able to maintain stability regardless to the delay in the communication channel [30]. The wave variables were also extended with the passivity formalism [1]. However, a significant improvement of a force projection was achieved by the four-channel architecture of the communication channel [6, 12]. Finally, the four-channel communication system was equipped with an adaptive controller which estimated control parameters of force and position channels simultaneously [36].

XXI century is a domain of control schemes based on: sliding mode controllers [19], fuzzy logic controllers [4], force-feedback communication channel frequency separation techniques [21], special methods for discretization of a sensor resolution [7], artificial neural networks [34] and adaptive controllers dedicated to variable and asymmetric time delays, which are using adaptive filtering methods [37]. However, it is important to pay attention that bilateral teleoperation systems feature three types of feedback with the operator: vision-feedback [28, 31], force-feedback [5] and combination of vision-feedback and force-feedback [5, 10, 29, 34, 36]. Remotely controlled devices can be controlled by operator's motion scanners [11, 29], which in a special case are exoskeletons for upper limb [24], by gesture control techniques [15, 20] or by voice control methods [32, 33]. And also methods, which are dedicated to real-time monitoring of remote environment [16–18]. Also an important classification of bilateral teleoperation systems with force-feedback are systems, which using force sensor [2, 5, 11, 21], and devices without force sensors also known as a sensor-less or self-sensing techniques in the telemanipulation field [22–27, 29, 34, 35]. The sensor-less teleoperation systems group usually is based on impedance control methods [8], and the inverse modeling techniques to obtain correct value of force in the force-feedback communication channel [24, 26, 35]. Inverse models are represented frequently by artificial neural networks [34], nonlinear autoregressive model with exogenous inputs (NARX) [24], and by micromanipulators which are using reversal processes that occur in piezo-crystals [22].

The paper addresses the transport delay problem in a sensor-less control scheme based on a dynamic inverse modeling procedure, which allows the system to estimate environmental force affecting the Slave manipulator. The dynamic inverse model used in the control unit was extended with proposed prediction blocks. The single prediction block has been a phase shifter with a specific characteristics. The specific feature of the prediction block is a strongly linear and positive phase diagram in a useful frequency spectrum, which allows the system to predict the manipulator's motion with a close to constant time shift. The gain of the block is close to the a unity, when system is operating also in a useful frequency spectrum. The proposed nonlinear inverse dynamic model structure which nonlinearity included the modified Stribeck friction model was validated on a 1-DOF hydraulic manipulator. The experiment and simulations confirmed the effectiveness of the predictive nonlinear inverse model, by reducing the time shift error between measured and simulated control signals.

2 Problem Statement

The primary issue of inverse models used in a control unit of any device is always present transport delay [31]. Usually, a control scheme based on differential equations will cause a delay between measured and simulated signals. Thus, the delay between signals will result in a noise appearance in the force-feedback channel with an amplitude that may destabilize the system even in free-motion operation—Fig. 1.

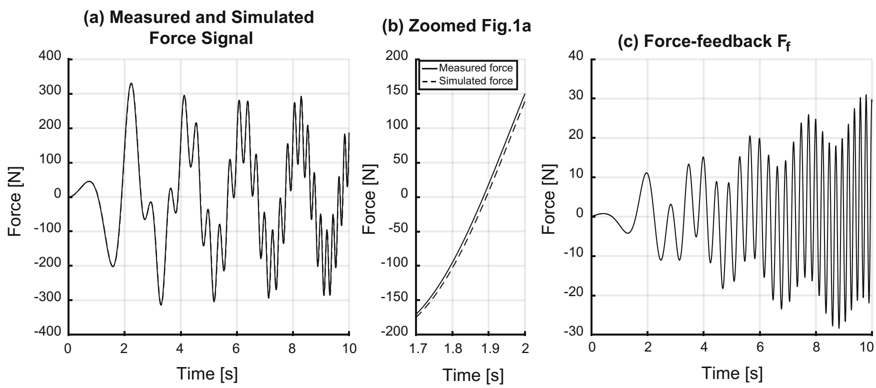

Fig. 1 **a** Measured and simulated force, **b** zoomed (**a**), **c** force-feedback channel

The seemingly unnoticeable delay between two signal in Fig. 1a zoomed in Fig. 1b caused deformation of force and could destabilize the entire bilateral system with a force-feedback communication channel. This difference, which has been calculated from the control signal Fig. 1c is caused by a 10 ms transport delay. The effect of a dangerous noise in the force-feedback channel increases its negative impact on the force transparency. This feature is a one of the primary concerns of the sensor-less control schemes based on inverse modeling techniques, but it is also a motivation of a research presented in the paper.

3 The Prediction Block

This section presents an approach for minimizing the effect of a transport delay in the communication channel and it is based on a prediction of inputs of an inverse model by a simple phase shifter. The prediction block minimizes the transport delay effect of a control unit, an actuator, objects and sensors directly in the control unit of a Slave subsystem. Schematic diagram of the Master-Slave system with force-feedback is presented in Fig. 2a.

The system structure contains 3 specific objects: the operator block which controls the position of the Master subsystem (motion scanner) by affecting it with human force F_h. The Master subsystem transfers its position x_m to the Slave subsystem. The control unit of the Slave subsystem seeks to obtain the position of Master subsystem by the Slave subsystem $x_s = x_m$. By the force-feedback communication channel F_f environmental force influence F_e is being transfer back to the Master subsystem. The second task of the motion scanner is to deliver the force from the force-feedback communication channel back to the operator $F_f = F_e$. Theoretically the value of the force $F_m = F_e$ [24], but for real devices, the F_m force delivered by an actuator of the Master subsystem to the operator strongly depends on the inverse model accuracy. In the case of the considered system, 3 types of feedback with the operator can be used: force-feedback F_m (F_f), vision-feedback of the Master Subsystem position $x_{m,}$ and the vision-feedback of the Slave subsystem position x_s. The Slave vision-feedback can be useful only, when both subsystems are in close range or when an image is being transmitted online from the cameras around the Slave subsystem placement.

During the analysis of the control schemes based on the NARX model [23, 24] and the first introduction of the prediction techniques [25–27, 29], in the paper a

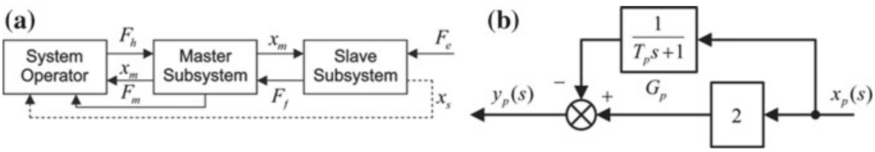

Fig. 2 **a** Master-Slave system analyzed, **b** the prediction block

prediction block with its time constants T_p estimation method is proposed. The prediction block and its structure was developed during the analysis of the Smith prediction control [9]. The proposed structure of the prediction block is presented in the Fig. 2b. The transmittance characterizing the automation structure in the Fig. 2b is described by a ratio of an output signal $y_p(s)$ and an input signal $x_p(s)$ and is given by Eq. (1):

$$y_p(s)/x_p(s) = \left(2T_p s + 1\right)/\left(T_p s + 1\right) \tag{1}$$

where s is the Laplace operator. Examining the transmittance (1) in the frequency domain it has to be paid attention to the amplitude (Fig. 3a) and phase diagrams (Fig. 3b) of the prediction block presented in the Fig. 3. The prediction block depending on the T_p constant is able to linearly shift a phase of an input signal, resulting in a constant time shift, but only in a useful frequency spectrum—Fig. 3b. Unfortunately, the prediction block like any phase shifter is a cause of a gain of the input signal amplitude, but in the useful frequency range, the gain is close to a unity—Fig. 3a. The useful frequency spectrum is understood to be the achievable for a human motion. Scientific literature gives a limit of a 6 Hz [13] but for the inverse modeling technique it was decided to increase the limit to 10 Hz, to leave a bigger margin of error for the inverse model output signal. The prediction ability was confirmed also in a simulation of the first order transfer function with $T = 0.001$ parameter which response was predicted. Simulations results in time domain are presented in the Fig. 3c.

Both frequency diagrams in Fig. 3a and b, and the step response in Fig. 3c are the proof of a predictive capabilities of the prediction block. But, it is important to note that the prediction block is sensitive to a noise and changes of a signal derivative sign $x_p(t)$. An amplitude of a noise will be increased twice, when using only one prediction block. When using more of the prediction blocks in a serial connection,

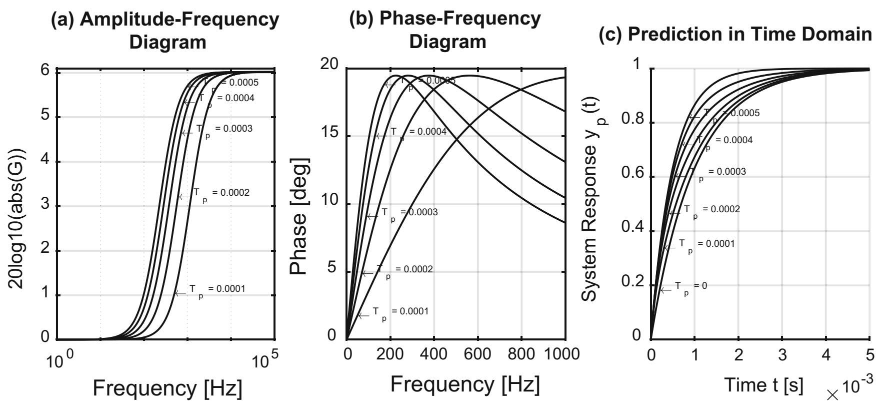

Fig. 3 **a** Amplitude-frequency, **b** Phase-frequency diagrams of the prediction block, **c** Step response prediction of a first order transfer function response

the gain depends on a number of prediction blocks used by 2 to the power of the number of prediction blocks.

4 Inverse Model with Prediction of Input and Output Signals

Theoretical analysis carried out in the previously published papers [23–26] proved that, the ideal response of a sensor-less control scheme in the force-feedback channel is only reachable, when the system is equipped with an ideal inverse model. In practice, obtaining an ideal inverse model of any subsystem is impossible.

In the paper, it was decided to estimate an environmental force based on the control signal, which is well-known. The inverse dynamic model G^{-1} in this case, estimated a control signal which is required for free-motion of a Slave manipulator, and based on the position x_s in a single joint. The estimated control signal was then subtracted from the well-known control signal, which was applied to the object—Figure 4.

The control unit scheme describes the Slave subsystem with a dual channel based communication technique. The Slave subsystem consists of a controller $K_c(s)$, an actuator $G_a(s)$, an object $G_o(s)$ and a sensor $G_s(s)$ transfer functions. The actuator was described by three parameters, a gain K_a, a transport delay T_1^a and a constant parameter of a first order inertia object T_2^a. The object describes the 1-DOF Slave manipulator body and is characterized by two parameters, a mass M_s and a linear viscous damping h_e. The sensor transfer function is similar to the actuator's transfer function and it is described by three parameters, a gain K_s, a transport delay T_s^1 and a constant parameter of a first order inertia object T_s^2. The estimation block consists the inverse model G^{-1}, a low-pass filter $G_f(s)$ with a parameter T_f and a gain K_a, same as in the actuator's transfer function. In the case of a known inverse model, which describes Slave subsystem in the Fig. 4, by the Eq. (2):

$$G^{-1} = e_{1\ \ 1}^{s(Ta+Ts)}\left(T_2^a s + 1\right)\left(T_2^s s + 1\right)(h_e + M_s s)s/\left(K_a K_s\left(T_f s + 1\right)\right), \quad (2)$$

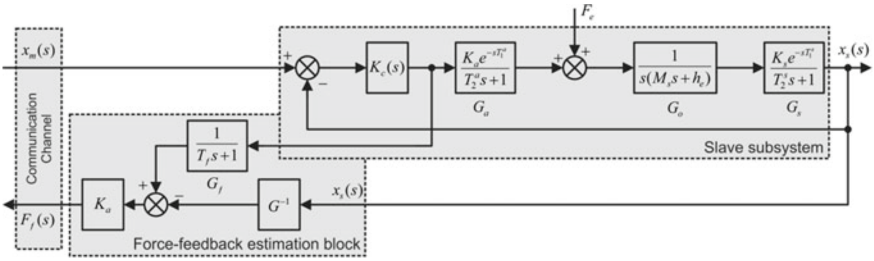

Fig. 4 Control unit scheme of the Slave subsystem with force-feedback estimation block

the difference between the object control signal and the estimated control signal in free-motion, increased by the gain K_a gain describes the force $F_f(s)$ in the force-feedback communication channel, and is equal to the environmental force impact $F_e(s)$ (3):

$$F_f(s) = F_e(s). \tag{3}$$

However, the presence of a positive parameter in the exponential functions makes the G^{-1} model (which describes the process) impossible for physical interpretation and also without a possibility of implementation in a control unit.

To minimize the effect of a transport delay in the force-feedback communication channel, two prediction blocks have been implemented into the structure of the inverse model replacing the exponential function with a positive parameter. Also, prediction blocks replaced first order inertias with parameters T_2^a and T_2^s, to minimize the noise effect of a high order numerical differential calculation. However, to equalize the degree of polynomials in the denominator and the numerator it has been added subsequent first-order inertial block with parameter T_d which has been working as another low-pass filter. The proposed inverse model is described by an Eq. (4):

$$G^{-1} = (h_e + M_s s)s/\big(K_a K_s\big(T_f s + 1\big)(T_d s + 1)\big)\big(2T_p + 1\big)$$
$$\big(2T_p + 1\big)/\big(\big(T_p s + 1\big)\big(T_p s + 1\big)\big). \tag{4}$$

The output signal of the inverse model $K_c^s(s)$ which control unit should apply to the actuator, is a signal $K_c(s)$, when the Slave manipulator performs movement in a space without the environmental influence. In practice, the estimated control signal approximates signal controller K_c described by $K_c^s(s) \cong (x_m(s) - x_s(s))K_c(s)$, which is affected by the transport delay. However, to obtain the parameter $T_{p,}$ it is required to find a solution of an equation describing the force-feedback estimation block presented in the Fig. 4 under two conditions. First condition concerns situation when environmental force is not applied to the manipulator's body: $F_e(s) = 0$ and second condition when zero value of force in the force-feedback channel is expected: $F_f(s) = 0$. Under these two conditions, equation describing subsystem in the Fig. 4 takes the following form (5):

$$(x_m(s) - x_s(s))K_c(s)G_f(s) + G^{-1}\big(s, T_p\big)x_s(s) = 0, \tag{5}$$

where the $G^{-1}(s, T_p)$ is the inverse model (5) as a function of two variables; the Laplace operator and the parameter T_p. Unfortunately, the parameter T_p even for such a simple example as the presented one, is described as a function of the Laplace operator: $T_p = T_p(s)$. During the research carried out with multiply model structures it was discovered that optimal value of T_p has been always obtained for the pulsation value which boundary was tending to zero. After that, it was proposed to calculated the limit of the T_p as a function of Laplace operator s, when s tends to zero—Eq. (6):

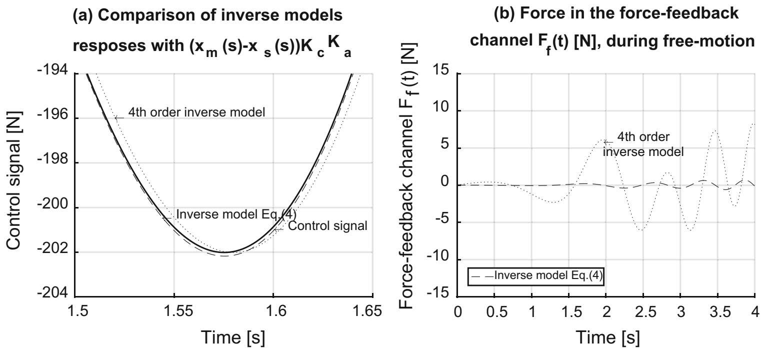

Fig. 5 The Subsystem Slave simulation results **a** force prediction, **b** force-feedback channel

$$T_p = lim_{s \to 0} T_p(s). \tag{6}$$

Currently, Eqs. 5 and 6, is a proposition for the T_p parameter estimation. In a future, it is planned to introduce a proof that will confirm this description, which was given in the paper.

Subsystem in the Fig. 4 was analyzed during multiple simulations. The comparison of the linear model—Eq. (4) and the standard 4th order transfer function with an equal degree of the polynomial in the numerator and the denominator. The simulation research was carried out on the subsystem Slave, and for the following data: $K_c = 100$; $K_a = 1$; $K_s = 1$; $T_1^a = 0.002$; $T_2^a = 0.002$; $M_s = 10$; $h_e = 1$; $T_1^s = 0.002$; $T_2^s = 0.002$; $F_e = 0$; $T_d = 0.0005$; $T_f = 0.0005$ and $x_m(t)$ was a harmonic signal with variable frequency in the range of 0.1–10 Hz. The results are presented in the Fig. 5.

Simulation results confirmed, that the inverse model which structure included prediction blocks was able to predict the control signal with higher accuracy, than the same order model was obtained during standard identification techniques. Two prediction blocks were able to replace two first order inertia parameters like T_1^a and T_1^s, and also minimize the effect of a transport delay present in the system. The results are confirmed by the diagram in the Fig. 5a, where the inverse model with prediction blocks response is much closer to the original control signal, than the standard 4th order inverse model response. This significant difference in identification techniques is especially visible in the force-feedback communication channel—Fig. 5b. The noise in the force-feedback channel $F_f(t)$ is barely visible for the proposed model when the 4th order inverse model obtained in the standard identification technique has caused a significant error of the force estimation.

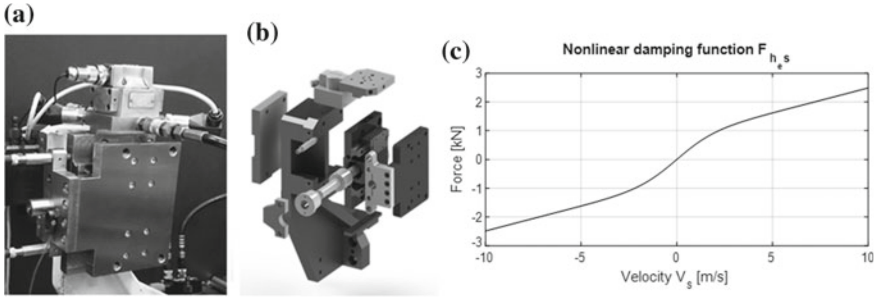

Fig. 6 **a** The experimental test stand **b** exploded CAD view **c** damping function

5 The Experiment

The method based on prediction of an input of an inverse model was validated on a hydraulic 1-DOF linear manipulator presented in the Fig. 6.

The experimental 1-DOF manipulator has been actuated by the 760s MOOG servo-valve. The test stand was equipped with two independent pressure sensors placed in both piston chambers. The position was measured by two inductive sensors. The measured and estimated control signal by the inverse model was the valve current. The inverse model has a structure presented by the Eq. (4) but included a nonlinear component describing the damping force F_{hes}, which is given by the Eq. (7):

$$F_{hes}(t) = \left(\left(1 + e_s^{-v(t)}\right)\right)^{-1} - 0.5 + 0.1v_s(t) + 0.00045|v_s(t)|v_s(t))h_{e,} \tag{7}$$

where $v_s(t) = dx_s(s)/dt$.

The damping coefficient h_e, was identified at level of a 1.61 kNs/m. The mass was identified at 6.8 kg. The proposed damping function has not been chosen accidently. The noise present in the velocity signal has caused a significant amplitude of disturbance, when standard Stribeck friction model was used [3]. The nonlinear damping function is presented by a diagram in the Fig. 6c.

The identified model was expanded by two prediction blocks and implemented in the control unit. The identification of the T_p coefficient was carried out iteratively. For two prediction blocks, the T_p coefficient was identified at 0.0018. Unfortunately, for the remaining transport delay, responsible was the step change of a friction force described by the Stribeck model, but it is barely visible amid the noise. The implementation of prediction blocks allowed to minimize the current mean absolute error from 0.55 to 0.39 mA when chirp signal response was used as a comparison input signal. This is a significant difference which allowed to reduce the estimation error about 30%. The ability of proposed inverse prediction model is presented in the Fig. 7.

Diagrams presented in the Fig. 7 are the best proof of the proper functioning of the method. The advantage of the method is especially visible for low frequency

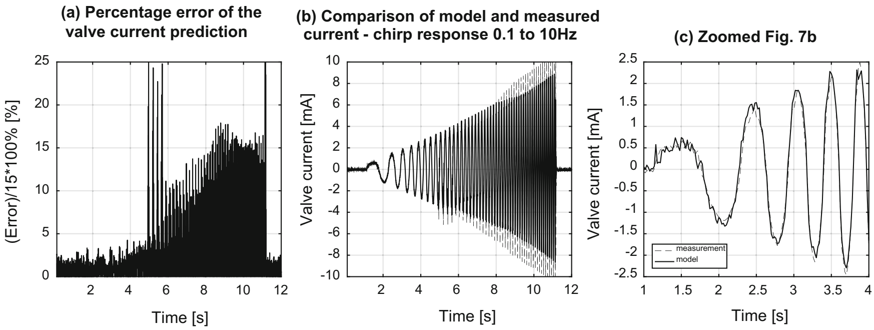

Fig. 7 **a** Percentage absolute error of the valve current prediction, **b** comparison of model and measured current data–chirp response 0.1–10 Hz, **c** Zoomed (**b**)

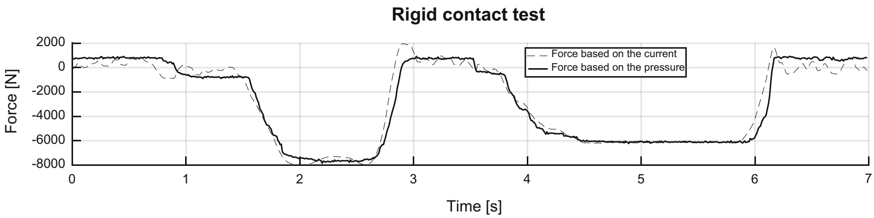

Fig. 8 Force in the force-feedback communication channel during rigid contact test

spectrum, when error is at the level of the noise—below 5% relative to maximum possible valve current—15 mA. The ability of prediction allowed the system to maintain the stability even during a rigid contact situation task by minimizing the aggregate delay of the system in the force-feedback communication channel. The force in the force-feedback communication channel during a rigid contact task is presented in the Fig. 8.

During the rigid contact test, the operator was obliged to move the manipulator body until the piston will reach its maxim possible position. The operator forced twice the remotely controlled manipulator to interact with its movement boundaries, with different force interaction. The method allowed the system to predict the environmental force up to 200 ms faster, than it could be sensed by the pressure sensor during free motion (Fig. 8, time period from 0.5 to 1 s). It is important to note that the force value in the force-feedback channel was reduced a hundred times, because the hydraulic manipulator was able to generate a force of a 20 kN. Also during the identification procedure of the inverse model, it was carried out a standard identification procedure of a 4th order inverse model, not based on the signal prediction technique. Unfortunately, for all collected data, the model remained unstable and the comparison could not be taken into account.

6 Conclusion

The paper presents a novel approach to a control design in bilateral and sensor-less teleoperation systems based on the prediction of an input and an output of an inverse model. The technique was based on prediction blocks which each prediction block was a phase shifter with specific properties. Alike simulations and experiments are the proof of an advantage of the technique over standard identification methods. The method allowed the introduction of significant simplifications of the model while accuracy of the prediction was improved. The inverse model was used in the control unit of the test stand and series of tests were carried out. Experimental results confirmed that the system equipped with the proposed method is able to predict the environmental force impact with higher accuracy then the standard identification technique.

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