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Stabilization Of Teleoperated Systems With Stochastic Time Delays Using Time Domain Passivity Control

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Abstract: This work describes the application of Time Domain Passivity Control to the stabilization of a one-degree-of-freedom teleoperation system in the presence of stochastic time delays. A non-linear Kalman filter based predictor provides recursive estimates of remote energy which, in conjunction with the master-side energy of a network 2-port, give real-time estimates of net energy across the given port. These estimates are used to design time-varying stabilizing passivity controllers. Beta distributed time delays are predicted using one-step ahead 1^{st}-order predictor.

Keywords: Time Domain Passivity Control, Stabilization, Time Varying Delays, Teleoperation

1 INTRODUCTION

In many of the present day teleoperation systems, a computer network serves as the basis of communication and because of the presence of time delays in such a setup, the stability is compromised[1]. Force feedback in teleoperation turns the unilateral control scheme to a bilateral one. A survey outlining research and fundamentals of bilateral teleoperation can be found in Hokayem et. al.[2]. Since the identification of stability problem in bilateral teleoperation[3], different solutions have been proposed to solve it. Anderson and Spong[4] attempted the problem by passivation of the system using scattering theory. The teleoperation system can be represented as a network consisting of *n*-ports where master, communication block, and slave are represented by two-ports and the operator and environment by one-ports as shown in Fig. 1. Since their introduction, the wave variables[5] have been frequently used in time-delayed teleoperation. In [6], an AR delay predictor has been used to improve the performance of wave-variable based teleoperation. Despite the benefits offered by wave-variables, they still lack a direct physical meaning when compared to their counterparts like force and velocity. The absence of physical manifestation can pose challenges when designing controllers and it can be difficult to make use of intuitive insight in this process. Time Domain Passivity Control for stabilization of teleoperation systems involving haptic interfaces, was introduced by Hannaford and Ryu et. al. [7]. This approach does not require for the power variables to be transformed into wave-variables. Rather an easy to understand notion of energy is used to define passivity of the system. The proposed framework has been used in several applications to stabilize teleoperation systems, see e.g., [8]. A brief review of time domain passivity control is given in Section 2.

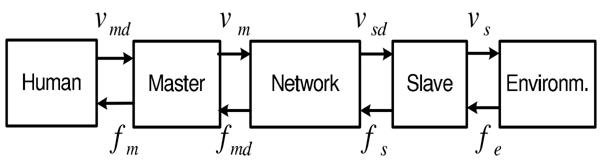

Fig. 1 A Telerobotic Network

If the communication network is taken as a component that is to be stabilized, the Time Domain Passivity Control approach can be applied to it. However, in the presence of time delays, it becomes impossible (i) to compute, and (ii) to convey the energy information, in a timely fashion, from both sides across the communication channel to online passivity controller design block which, in our case, is located on master side. This problem can be solved through i) estimating the current RTT(Round Trip Time) between master and slave, and ii) prediction of energy on the remote side of the network 2-port based on the estimated RTT. We use a linear 1-step ahead predictor to estimate the varying time-delays. On the slave side, a Kalman filter is used to recursively estimate the parameters of transfer function from the slave velocity to the environment force ($\mathscr{L}[f_s(t)/v_{sd}(t)]$). The obtained model is then used for $k-$*step ahead prediction of slave-side energy to be used in the calculation of the net energy across the network 2-port on master side*.

Derivatives of the net energy have been shown by authors in [9] to improve the transparency and to cut down the large corrective actions. Using the integrated net energy and its derivatives, we can achieve a network block such that Time Domain Passivity Control functions properly resulting in a stable teleoperation even in the presence of time-varying delays.

2 TIME DOMAIN PASSIVITY CONTROL

2.1 Passivity Theory

Passivity is concerned with energies of a system. Let E_i denote the initial energy of a system. Then this system will be called passive if:

$$E(t) = \int_0^t P d\tau + E_i \geq 0 \tag{1}$$

where $E(t)$ is the total energy of the system at time t. P denotes the net power at input and output ports. Assuming initial system energy to be zero, we get a well-known expression for energy of the system:

$$E(t) = \int_0^t P d\tau = \int_0^t \boldsymbol{u}^T \boldsymbol{y}\, d\tau \geq 0 \tag{2}$$

$\boldsymbol{u}$ and $\boldsymbol{y}$ represent system input and output vectors respectively. In the case of a telerobotic system, they are usually the causal pair $\boldsymbol{f}$ and $\boldsymbol{v}$. As an n-port is characterized by the causal relationship between effort f(force, voltage), and flow v(velocity, current) so, for a network 2-port, as shown in Fig. 1, the equation changes to:

$$\begin{aligned} E(t) &= \int_0^t P d\tau \\ &= \int_0^t (f_{md}(\tau)v_m(\tau) - f_s(\tau)v_{sd}(\tau))d\tau \geq 0 \end{aligned} \tag{3}$$

Signs should be carefully selected in this expression. Here we are considering f_{md}, v_m to be input- whereas f_s, v_{sd} to be output-variables.

Equation 3 means that a passive system must not generate energy by itself. It can only dissipate the input energy or in ideal conditions can function as lossless channel in which case $E(t) = 0$.

2.2 Time Domain Passivity Control

As described in Section 1, passivity can be guaranteed using different control techniques to manipulate the ports of an active system. Time Domain Passivity Control[7] uses the direct notions of energy and power variables. For a discrete case, on a network 2-port, as given in Fig. 1, a passivity observer can be designed as:

$$E_{obs}(n) = T_s \sum_{k=0}^{n} (f_{md}(k)v_m(k) - f_s(k)v_{sd}(k)) \tag{4}$$

With sufficiently small T_s, $E_{obs}(n)$ closely matches the system energy at instant t_n. However in this paper, another method is presented in Section 3.3 to estimate energy more refinely and even in cases when inter-arrival spacing is not equal. In normal passive operation, $E_{obs}(n)$ should always be positive. In cases when $E_{obs}(n) < 0$, passivity observer indicates that the system is generating energy and has gone active. Generally, once the system is regarded as an active port, a passivity controller must be engaged to dissipate the excess energy. Placement and configuration of a passivity controller depends on the causality of the port.

Passivity controller α_m dissipates energy on an impedance causality (master side) and α_s on an admittance causality (slave side), see Fig. 2. Computation of these controllers depends on the observed energy value $E_{net}(n)$. The results of Ryu. et. al.[7] are used as a basis in this work.

3 TIME DOMAIN PASSIVITY APPLIED TO DELAYED TELEOPERATION

In order to make use of the Time Domain Passivity Control framework, given in Section 2.2, to stabilize a delayed telerobotic system, one needs to compute master and slave energies, in real-time without delay. However, if the controller design is carried out on master side, the real-time value of slave energy is unknown because of the delay. To overcome this issue, an energy prediction based approach is used.

In order to measure energy on slave side, we need to measure v_{sd} and f_s, see Fig. 2. Out of these two, $v_{sd}(t)$ can be determined given knowledge of RTT and of the forward gains, if any. However computation of $f_s(t)$ requires the actual response of the combined transfer function from $v_{sd}(t)$ to $f_s(t)$ or $\mathscr{L}[f_s(t)/v_{sd}(t)]$.

As the environment and slave conditions may change over time, so an offline identified model is not a promising solution. In this case, we can design a recursive model of remote system which includes both slave and the environment. This model will be estimated online, the parameters of which would be computed recursively using non-linear Kalman filtering as given in Section 3.2. Then the predictor can, with the help of this estimated model, predict $\hat{f}_s(t)$ using $v_m(t)$ and the delay information. Once estimated, $\hat{f}_s(t)$ can be used for computation of α_s, the passivity controller, as if no delay existed in the forward channel. In addition, energy derivatives can be used to recognize a decrease in the net energy of the system. This information is then used, as described in Section 3.4, to design passivity controllers that offer considerable gain in velocity tracking.

3.1 Generation and Prediction of Time-Varying Delays

The stabilization scheme described in Section 3 depends on the knowledge of time delay in order to estimate the net value of energy, so prediction of RTT is an integral part of this approach. Mirfakhrai and Payandeh[6] proposed an AR-model based approach using parameter lookup tables to predict delays throughout different times of day. Ye et. al.[10] maintain that $RTTs$ have high correlation and given enough observations during certain times of days and weeks, a reliable model can be constructed for their prediction. Yang et. al. [11] have given a good survey of methods in use for the prediction of Internet end-to-end delays. It has been reported in literature[12], [13] that Internet delays roughly follow a beta distribution

Keeping in view the results of [12], [13], [6], [14], it can be safely assumed that Internet time-delays in a given teleoperation setup over Internet can be predicted to a reasonable degree of accuracy provided the knowledge of traffic over sufficient period of time. Consequently in this work, the simulation delays are generated using following beta pdf around a likely mean value:

$$f(x; \alpha, \beta) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1}(1-x)^{\beta-1} \tag{5}$$

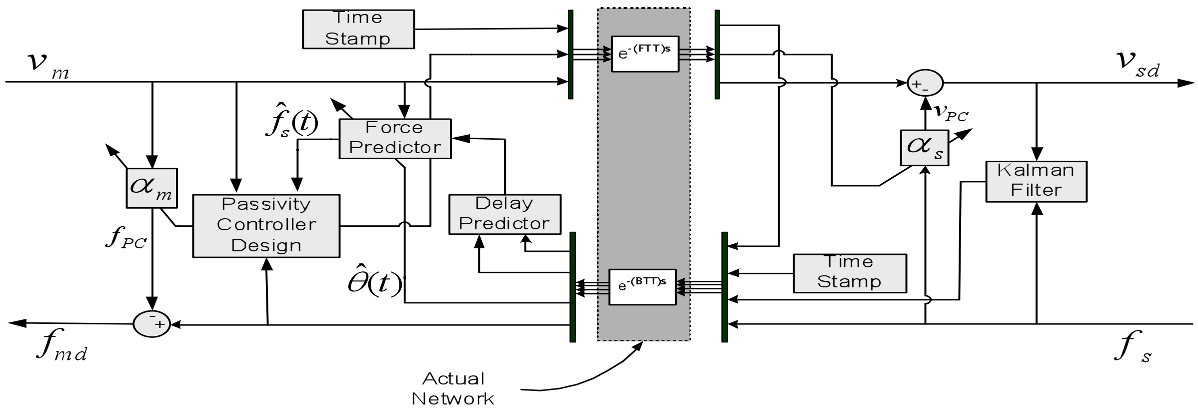

Fig. 2 Passive network 2-port in the presence of variable time delays using Predictive Time Domain Passivity

where $0 < x < 1$ and:

$$B(\alpha, \beta) = \int_0^1 x^{\alpha-1}(1-x)^{\beta-1}dx \tag{6}$$

In a practical setup, the mean value of this distribution would come from and would change based on the network traffic analysis. To estimate these $RTTs$, we use a first order predictor. As noted in [11], RTT cannot be estimated by just doubling the FTT(Forward Trip Time) or BTT(Backward Trip Time), so we have chosen to predict the RTT based on the previous measurements of the same. In such a case, if required, separate predictors would be required for each FTT and BTT. If $RTT(n)$ is described as $\Delta(n)$, then one-step ahead predictor based on previous two values of RTT can be written as:

$$\hat{\Delta}(n+1) = (\Delta(n-1) - \Delta(n-2))\rho(n) + \Delta(n-2) \tag{7}$$

where

$$\rho(n) = \frac{t_n - t_{n-2}}{t_{n-1} - t_{n-2}} \tag{8}$$

It should be noted that this prediction is subject to upper and lower bounds of RTT as well as it can be seen that equally spaced RTT measurements are not required.

3.2 Non-linear Recursive Estimation of Slave Energy

To estimate the slave energy in real-time requires a non-linear recursive estimator of the parameters of slave robot as well as of environment because these parameters can change over time. A linear estimator, Kalman filter in our case, is used and it is postulated that the true parameter vector is not constant but rather varies like a random walk.

In this case, if $\hat{\theta}(t)$ denotes the parameters of online predictor, the recursive parameter update equation can be written as:

$$\hat{\theta}(t) = \hat{\theta}(t-1) + L(t)\left[f_s(t) - \hat{f}_s(t)\right] \tag{9}$$

or

$$\hat{\theta}(t) = \hat{\theta}(t-1) + L(t)\left[f_s(t) - \psi^T(t)\hat{\theta}(t-1)\right] \tag{10}$$

where

$$\theta(t) = [\beta_1(t)\ldots\beta_3(t) \;\; \gamma_1(t)\ldots\gamma_3(t)] \tag{11}$$

for the following 3^{rd} order model for prediction of $f(t)$:

$$\hat{f}_s(t) = -\sum_{i=1}^{3}[\beta_i(t)f_s(t-i)] + \sum_{i=1}^{3}[\gamma_i(t)v_{sd}(t-i)] + e(t) \tag{12}$$

The parameter estimation model can be described as:

$$\theta(t+1) = F(t)\theta(t) + w(t) \tag{13}$$
$$f_s(t) = H(t)\theta(t) + e(t) \tag{14}$$

where in our case, $F(t) = I$, and $H(t) = \psi^T(t)$. $\theta(t)$ is the parameter vector at time t, and $\psi(t)$ is the regressor vector. $w(t)$ is white Gaussian noise and serves to help drift the parameter vector in the manner of a random walk. $e(t)$ is white noise. The above equations can be rewritten as:

$$\theta(t+1) = \theta(t) + w(t) \tag{15}$$
$$f_s(t) = \psi^T(t)\theta(t) + e(t) \tag{16}$$

where

$$Ew(t)w^T(t) = R_1(t) \tag{17}$$
$$Ee(t)e^T(t) = R_2(t) \tag{18}$$

In such a case, equation (9) can be computed as[15]:

$$L(t) = \frac{P(t-1)\psi(t)}{R_2(t) + \psi^T(t)P(t-1)\psi(t)} \tag{19}$$

$$P(t) = P(t-1) - \frac{P(t-1)\psi(t)\psi^T(t)P(t-1)}{R_2(t) + \psi^T(t)P(t-1)\psi(t)} + R_1(t) \tag{20}$$

where $P(t)$ and R are output error- , and measurement error-covariances, respectively. $\phi(t)$ is the vector containing input and output values at time t.

Using the above mentioned method, the non-linear joint model of the slave and environment can be estimated recursively. As a first attempt, a 2^{nd}-order ARX model was used. However simulations suggested that a 3^{rd}-order model best describes the dynamics of the system as well as smoothens the predicted energies considerably.

The non-linear estimator is placed on the slave side and gathers the input and output data directly from the slave. In this fashion, we reduce the probability of errors that can occur because of the passivity controllers, had the estimator been placed on the master side. The complete stabilization scheme using online estimation and $k-$step ahead energy prediction and variable time delay prediction is shown in Fig. 2.

3.3 Parabolic Real-Time Power Integration

Kalman filter provides recursively updated estimate of parameters $\hat{\theta}(t)$ through the network. Once we have the predictor parameters, the inputs trapped in the delay i.e., $[v_m(t-\hat{\Delta}(t+1|t))\ldots v_m(t)]$ can be used in $k-step$ ahead energy predictor where $\hat{\Delta}(t+1|t)$ is the estimate of RTT at time $t+1$ given the RTT delay at time t as described in (7). The k^{th} output corresponds to current time t and is given as $\hat{f}_s(t)$ which is the predictive estimate of environment force.

This output is then used as following to recursively calculate the energy:

$$E_{net}(n) = \sum_{i=0}^{n}\left[\int_{t_{i-1}}^{t_i} P_a(\tau)d\tau - \int_{t_{i-2}}^{ti-1} P_d(\tau)d\tau\right]$$
$$where \quad P_d, P_a = 0 \,\forall\, t \leq 0 \quad (21)$$

Here $P_a(n)$ is the *actual* net power at the network 2-port without taking into consideration the energy dissipation and is given as:

$$P_a(n) = P_m(n) - P_s(n) \quad (22)$$

where $P_m(n)$ and $P_s(n)$ represent the power at the master and slave ports and are given as:

$$P_m(n) = f_{md}(n)v_m(n) \quad (23)$$
$$P_s(n) = \hat{f}_s(n)\hat{v}_{sd}(n) \quad (24)$$

As described earlier, $\hat{f}_s(n)$ is estimated based on the Kalman filter based predictor whereas $\hat{v}_{sd}(n)$ is computed as:

$$\hat{v}_{sd}(n) = v_m(n-\zeta(n)) \quad (25)$$

and

$$\zeta(n) = \lfloor \hat{\Delta}(n+1|n)/T_s \rfloor \quad (26)$$

where T_s is the sample time.

On the other hand, $P_d(n)$ in (21) is the energy that has been dissipated in the $(n-1)^{th}$ step through both master and slave passivity controllers:

$$P_d(n) = -\alpha_m(n-1)v_m(n-1)^2 - \alpha_s(n-1)f_s(n-1)^2 \quad (27)$$

As we are using Simpson's rule for discrete integration of energies, both P_a and P_d are assumed to follow a parabolic function in the last three samples. The integral of a fitted parabola yielding observed energy for P_a from time t_{n-1} to t_n is given as:

$$\int_{t_{n-1}}^{t_n} P_a(\tau)dt = \frac{a(t_n)}{3}(t_n^3 - t_{n-1}^3)$$
$$+\frac{b(t_n)}{2}(t_n^2 - t_{n-1}^2) + c(t_n)(t_n - t_{n-1}) \quad (28)$$

where $a(t_n), b(t_n)$ and $c(t_n)$ are the parameters of a parabola:

$$P_a(t) = a(t_n)t^2 + b(t_n)t + c(t_n) \quad (29)$$

that has been fitted through three points namely $P_a(t_{n-2})$, $P_a(t_{n-1})$ and $P_a(t_n)$. The last term in (21), i.e., $\int_{t_{i-2}}^{ti-1} P_d(\tau)d\tau$ can be evaluated in a similar fashion.

3.4 Design of Passivity Controllers

As formulated in Section 3, the effect of time-delay is cancelled in the calculation of passivity controllers, so their values are computed as given in Table 1.

Cases I and II dissipate negative energies when either of master or slave sides of the network 2-port is responsible for active behavior[7]. When both master and slave ports become negative, the previous energy value $E_{net}(n-1)$ is also used, as given in [7], to make, in our case, the slave side additionally conservative which belongs to Case 3 in table 1. It is to be noted that $E_{net}(n)$ and $\left.\frac{dE_{net}(t)}{dt}\right|_{t=t_n}$ are evaluated at each step based on the previous sampling interval and if found negative, respective corrective action is taken.

The calculation of α_s is based on estimated force information, which may contain noise, so the system response becomes quite noisy if α_s is used directly. To counter this problem, we suggest a low-pass filter for α_s which is designed to pass only those frequencies that are closer to the expected correction rate. The concept of filters in teleoperation is not new. Spong et. al.[16] reported that a digital implementation of a continuous time passive system may no longer remain passive/stable and would require the introduction of strictly causal and stable linear filters to ensure stability of sampled-data master/slave systems. In addition, simple low-pass filters can also serve to help limit the bandwidth utilization.

Cases 4 and 5 dissipate the additional energy symmetrically on both master and slave ports. These terms attempt at making the transmission as lossless as possible.

Case 6, different in its nature from all other cases, based on the real-time derivative of net energy dissipates energy even when apparently the network port is passive, but in reality is tending to approach an active behavior. This step ensures that the system will always dissipate energy and will always stay passive. To implement this feature, once *the derivative* $\left.\frac{dE_{net}(t)}{dt}\right|_{t=t_n}$ gets negative, we do not wait for *net energy* to become negative, rather this decrease in net energy is compensated immediately. However this may result in tracking errors because of additional damping. This effect can be compensated by appropriately scaling the input command.

4 SIMULATION RESULTS

In order to simulate the system, we generate stochastic time delays and observe the response of the system to a

Table 1 Calculation of passivity controllers

Case	Energy Variables' Conditions						Designed Controllers	
	$E_{net}(n)$	$\left.\frac{dE_{net}(t)}{dt}\right\|_{t=n}$	$P_m(n)$	$P_s(n)$	$E_{net}(n-1)+ (P_m(n)T_s)$	$E_{net}(n-1)+ (P_s(n)T_s)$	$\alpha_m(n)$	$\alpha_s(n)$
1	< 0	n/a	< 0	≥ 0	n/a	n/a	$-\frac{(E_{net}(n)/T_s)}{v_m(n)^2}$	0
2	< 0	n/a	≥ 0	< 0	n/a	n/a	0	$-\frac{(E_{net}(n)/T_s)}{\hat{f}_s(n)^2}$
3	< 0	n/a	< 0	< 0	< 0	< 0	$-\frac{P_m(n)}{v_m(n)^2}$	$-\frac{(E_{net}(n-1)/T_s)+P_s(n)}{\hat{f}_s(n)^2}$
4	< 0	n/a	< 0	< 0	≥ 0	< 0	0	$-\frac{(E_{net}(n-1)/T_s)+(P_s(n)-P_m(n))}{\hat{f}_s(n)^2}$
5	< 0	n/a	< 0	< 0	< 0	≥ 0	$-\frac{(E_{net}(n-1)/T_s)+(P_m(n)-P_s(n))}{v_m(n)^2}$	0
6	≥ 0	< 0	≥ 0	≥ 0	n/a	n/a	0	$-\frac{\left.\frac{dE_{net}(t)}{dt}\right\|_{t=n}}{\hat{f}_s(n)^2}$

velocity command on one-degree-of-freedom master and slave arms. Environment model uses a stiffness constant $K = 5N/m$. The damping constant is $0.5N.s/m$. Master arm uses a force control loop to output the reflected force from the environment while slave arm uses velocity control to follow the operator commands. Velocity command is set to a sine wave with an amplitude of $0.25m/s$ and a frequency of $2Hz$. Sampling time is set at $10ms$.

Figs. 3(a)-3(b) show the teleoperation system when simulated without proposed stabilization scheme in the presence of stochastic time delays following the pdf given in (5) using $\alpha = 8$ and $\beta = 30$ for both FTT and BTT. The mean value of the RTT is $422ms$. The net energy in the system is growing negative and has made it unstable. The same setup using Time Domain Passivity Control as described in Section 3 is now simulated and the results showing command and slave velocities as well as the energies in the system are shown in Figs. 4(a)-4(g). It can be seen that the system is now stabilized for the given range of stochastic time delays. The value of net energy in these figures is positive which is a clear sign of passivity and hence stability. In this simulation, 95% of the $RTTs$ lie between $219ms$ and $602ms$, and the mean value is $410ms$. Fig. 4(g) shows good force prediction by non-linear Kalman filter based predictor. Energy regulation in terms of velocity modification in order to achieve stabilization by slave passivity controller is shown in Fig. 4(e).

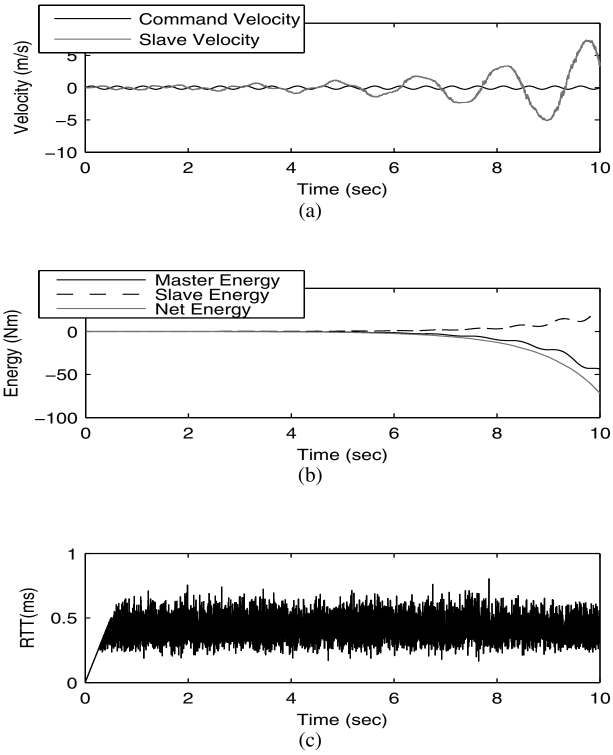

Fig. 3 (a) Command and slave velocities, (b) Energies in continuous time, (c) $RTTs$

5 CONCLUSION

It has been shown that Time Domain Passivity Control can be used to stabilize delayed teleoperation in the presence of stochastic time delays. Meaningful prediction of remote energy poses serious challenges when the environment parameters change rapidly or the variance of $RTTs$ increases. Bandwidth of the communication channel also plays an important role. Nevertheless, the concept is self-explanatory and accompanied simulation results sufficiently prove the efficacy of the approach presented.

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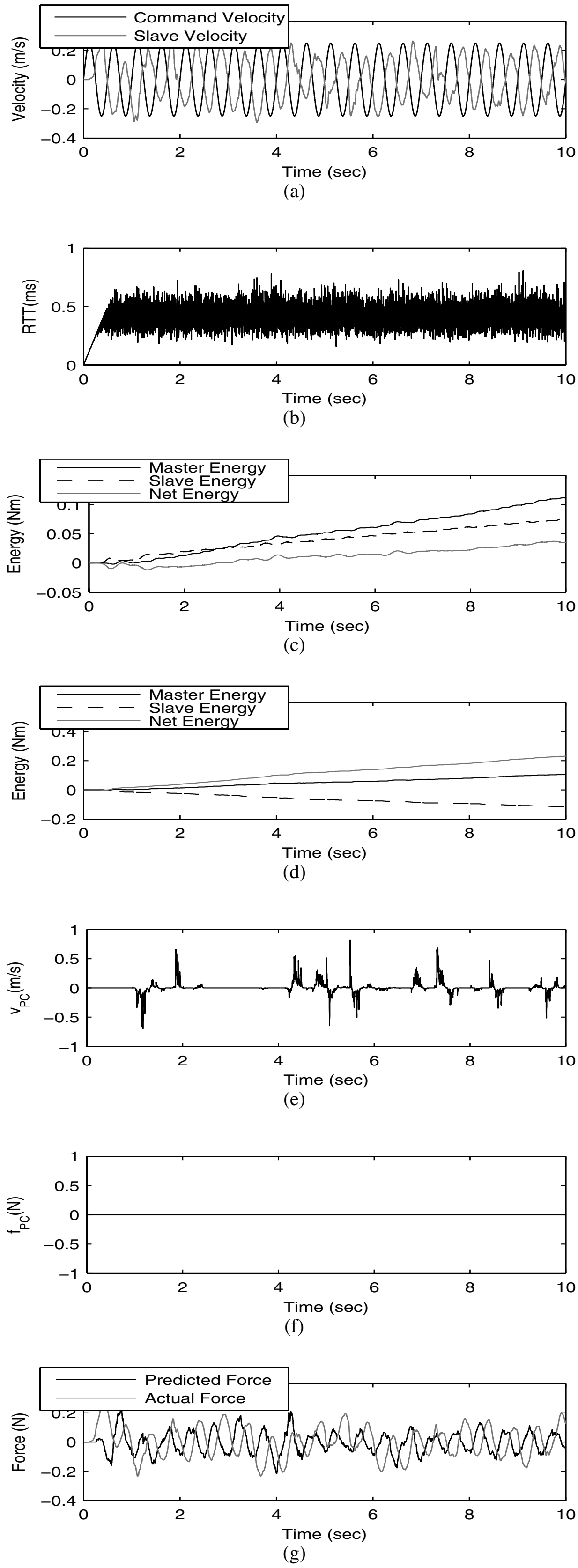

Fig. 4 (a) Command and slave velocities, (b) RTT, (c) Energies in continuous time, (d) Parabolically integrated discrete energies, (e) v_{PC}, (f) f_{PC}, (g) Predicted and actual environment forces