A NOVEL DUAL-USER SHARED TELEOPERATION TRAINING METHOD WITH MULTIPLE DOMINANCE FACTORS

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ABSTRACT

In this paper, we propose a novel training dual-user shared method with multiple dominance factors for a better knowledge of operational force and impedance variation during the teleoperation process. First we build the model of single user and dual-user training teleoperation system with operational force. Then we modeled the unstable environment and drew the motion trajectory using the Phantom and Omega manipulators considering the influence of time delays. By analyzing the experimental data during operation training tasks we draw the conclusions: the position errors decrease with the increasing of training times which is concluded from the single user teleoperation process. For dual-user teleoperation training process, the dominance factors varied from the initial values to the value $\alpha_3 = 1$, which is controlled by the trainee, the results reveal that choosing appropriate dominant factors affects the operation precision and stability.

1 INTRODUCTION

In large time-delayed bilateral teleoperation, while there is a long distance between master operator and slave object, signal could delay a few seconds during communication inevitably, which have a significant effect on stability and operation performance in teleoperation. Stability is particularly important for human motion because of the large variability in consecutive performances of the same action, i.e. motor output variability, and because we perform most actions in interaction with the environment which may add variability.

As we solving models and prediction of operation time delay, it is necessary to train the operators because the time delay in communication of teleoperation will impact the operating effect significantly. The traditional training is for single person, which takes a long time. Collaborative teleoperation of multi-user systems has been studied for several years, which has been applied in area of robotic rehabilitation and surgical training, and dual-user teleoperation system is the simplest one that is controlled by two users. The basic architecture of dual-user shared control is first proposed by Nudehi [1] and Behzad [2], which is consisted of two master robots and a slave robot, and the control authority is shared between the masters through the dominant factor. Through adjustments of several dominant factors, operators can provide the constraint and correction for operation of each other.

Nowadays, the problems of kinesthetic performance and control methods have been studied by several researchers. In [2]-[4], Khademian and Hashtrudi et al used measured functions such as transmitted impedance, transparency transfer function, range of achievable impedance and bilateral architecture distance transfer function et al to analyze the kinesthetic performance of dual-user teleoperation. In addition, they proposed the absolute stable condition for shared control architecture. Nudehi et al proposed the $H\infty$ control method for haptic collaboration without considering the kinesthetic feedback [1]. The $H\infty$-based multilateral force-position control architecture provides kinesthetic feedback between masters and the slave is proposed in [5].

Shahbazi made a study about control methods for dual-user teleoperation system under the influence of communication delay [6]. The robust control method with constant time-delay is also proposed. The adapting impedance control [7],[8] and sliding model [9] methods are put forward to the situation with unknown constant time delay.

To manipulate objects or use tools, one has to interact with the environment and compensate for forces arising from it. Ultimately, it is the interaction

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between our limbs and the environment that determines whether or not a movement will be stable [10]. While tasks such as opening a door involve a stable interaction with the environment, many common tasks, in particular, tasks involving tools are intrinsically unstable [11]. Drilling, carving and keeping a screwdriver in the slot of a screw are just a few examples of unstable tasks. Unstable tasks are more difficult to control than stable tasks, as neuromotor noise [12],[13] or material irregularities can cause the tool to slip unexpectedly to one side or the other.

Humans constantly adapt their movements to changes of internal and external conditions. Learning in novel environments, where environment interaction with the arm is stable, has been investigated extensively [14]-[17]. The experimental data show that subjects learn a feed forward compensation force necessary to overcome external dynamics. Learning in a divergent force field that produced an unstable interaction with the arm has been examined [18], and the results show that humans improve task performance and overcome instability by increasing the mechanical impedance of the arm selectively in the unstable direction. Altogether, these results suggest that humans form appropriate internal models to compensate for force and instability arising from the interaction with the environment.

Several algorithms have been proposed to model motor learning [18]-[21]. These learning schemes have been shown to work in single user operation tasks. However, very little dual-user operation with unstable tasks has been investigated so far. In this paper we apply the dual-user shared control architecture for training operators in teleoperation which involves two operators, the trainer and the trainee. We mainly studied the adjustment efficiency and effect of humans control impedance under dual-user and single slave control mode for unstable tasks.

The rest of the paper is organized as follows. We first model the operation process of bilateral teleoperation with time delay, and then the operation force updating algorithms were given. Second, two kinds of experiments were token under specific conditions, specifically single user and dual-user. The results were analyzed after experiments respectively and we drew several conclusions.

2 MODELS AND METHODS

Mathematically, we think of a teleoperation system as comprised of two robotic subsystems one or two masters and one slave that exchange signals (velocities and/or forces); in which the slave tries to mimic the behavior of the masters which in turn takes into account the input torques from the slave. A linear model of master/slave system can be written as,

$$\begin{cases} M_{mi}\dot{V}_{mi}(t) + B_{mi}V_{mi}(t) = F_{hi}(t) - F_{mdi}(t) \quad i = 1,2 \\ M_s\dot{V}_s(t) + B_s\dot{V}_s(t) = F_{cs}(t) - F_e \end{cases} \tag{1}$$

where $V_*(t) \in \mathrm{R}^n$ (*=m or s) are the velocity of the master i or slave endpoint, M_* and B_* are inertia and damping matrices of master i or slave, F_{hi} are users force affected on master robots, $F_{mdi}(t)$ are desired force that affected on the master i , $F_{cs}(t)$ and F_e correspond to the external forces exerted by controller of the slave side and the environment, respectively. $F_{mdi}(t)$ are different for single user and dual users architecture. When the slave is controlled by single user,

$$F_{md}(t) = F_e(t - T_1) \tag{2}$$

For dual-user architecture, the desired force is determined by slave and the other user, namely

$$\begin{cases} F_{md1}(t) = \alpha_1 F_e(t - T_1) + (1 - \alpha_1) F_{h2}(t) \\ F_{md2}(t) = (1 - \alpha_2) F_e(t - T_2) + \alpha_2 F_{h2}(t) \end{cases} \tag{3}$$

T_1 and T_2 indicate the communication time delay from master to slave respectively.

In [18]-[21] the control impedance is constant, and the control force is calculated by velocity of the end of robot arm. While in [22], the restoring force is calculated by the joint positions, which suits to requirement of human engineering accurately. Obviously, for teleoperation process, we only focus on the position and the outer force of the end of the arm, and the velocity can be calculated by the joint velocity, if the length of the upper arm and forearm are known. Then r_i is the restoring force corresponding to the position and velocity of the arm, which is generated by muscle elasticity r_{ei} as well as reflex force r_{ri} ,

$$r_i(X_{mi}(t), V_{mi}(t), X_{mi}(t)*, V_{mi}(t)*) = r_{ei} + r_{ri} \tag{4}$$

$X_{mi}(t)$ is the position of the arm, $V_{mi}(t)$ is the velocity of the arm, $X_{mi}(t)*$ and $V_{mi}(t)*$ are the trajectory in learned dynamics, ignoring the influence of the restoring force,

$$F_{hi}^*(t) = f(X_{mi}(t)*, V_{mi}(t)*) \tag{5}$$

Here, the desired values can be known after a period of training. For simplicity, the torque r_i is assumed to be produced by both reflex forces and muscle elasticity and can be modeled as linear functions of the trajectory deviation[21],

$$r_i = r_i(e, \dot{e}) \tag{6}$$

where $e = X_{mi}(t) - X_{mi}(t)^*$, $\dot{e} = V_{mi}(t) - V_{mi}(t)^*$.

Muscle elasticity is modeled as

$$r_e = K(e + \kappa_d \dot{e}) \tag{7}$$

where K is the intrinsic joint stiffness matrix which increases with torque.

Reflexes are modeled as

$$r_r(t) = G(e(t-T) + g_d \dot{e}(t-T)) \tag{8}$$

where G is the reflex gain matrix and T is the time delay.

For the slave side, Assuming that the time delay between the slave and masters are the same, then the desired value of $V_s(t)$ is influenced by both masters in dual-user shared control architecture.

$$V_{sd}(t) = \alpha_3 V_{h1}(t-T_1) + (1-\alpha_3) V_{h2}(t-T_2) \tag{9}$$

Then the sketch map of dual-user shared control method is presented as Figure 1 shows [23]. The structure is different from the one mentioned in [1]-[9], which is mastered by single dominant factor. As (3) and (9) shows, the architecture is controlled by three dominant factors $\alpha_i, i = 1,2,3$. It could be proved that the kinesthetic measuring performance is better than the ones of traditional dual-user shared control method by adjusting the dominance factors. For example, once the dominance factor α take 1 in traditional methods, one of the masters cannot communicate with the slave directly, while the one with multi-dominance factors can select the tracking target with more flexibility.

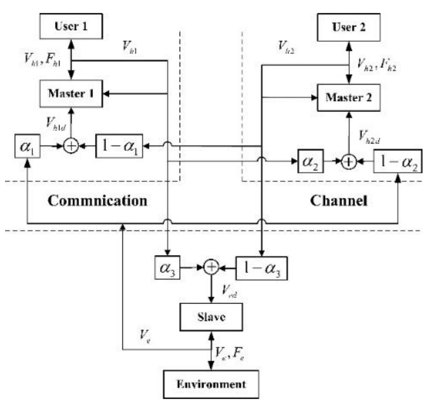

Figure 1: The system structure of dual-user shared control

Different from the impedance in [18]-[21], which is constant, while in fact, the outer force and impedance coefficients are updated in learned dynamics. According to the following learning law, the force $F_{hi}^{(j)}(t)$ will change with the training times j [22].

$$F_{hi}^{(j+1)}(t) = F_{hi}^{(j)}(t) + \alpha(r_e^{(j)} + r_r^{(j)}) \tag{10}$$

then the control force of the Slave is updated every time by changing the storing forces and output force formulated by the muscles.

3 EXPERIMENTS AND ANALYSIS

The experiment platform is consisted of two 3-DOF haptic devices (Phantom and Omega3.0) and a 3-DOF virtual visualized operational object, which is built by Visual Studio 2005 and Chai3D2.0. The system control laws are implemented in the MATLAB/Simulink environment and the slave point is generated with virtual feedback force. During the experiment, the slave and masters in X and Y directions are free, and the movement in Z axis is fixed. Here, we make a pair of compare experiments —single user single slave (SUSS) and dual-user single slave (DUSS) to measure the training effect of dual-user shared control method.

According to [22], the manipulation equipment is controlled in area of NF (null field), VF (velocity dependent field), CF (curl force field) and DF (divergent force field), and working in DF is the hardest for training [24]. Similarity, during the teleoperation process, the slave robot is controlled by the master side, the environment is not affected on the equipment directly but on the slave side.

Then the force affected by the environment is transmitted to the master side with time delay $T_1 = T_2 = 500\text{ms}$, so is the control signals produced by the master side. Therefore, we took two experiments in DF environment. A monotonic learning law can be depicted that a positive error produces a positive change of motor command and a negative error produces a negative change. To examine how such algorithms function in unstable interactions, we performed simulations for the DF (divergent force field).

The DF was implemented as

$$\begin{bmatrix} F_{ex} \\ F_{ey} \end{bmatrix} = k_d \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{11}$$

where x and y are the positions of the end of the arm. The potential force and its divergent force field are shown in Figure 2.

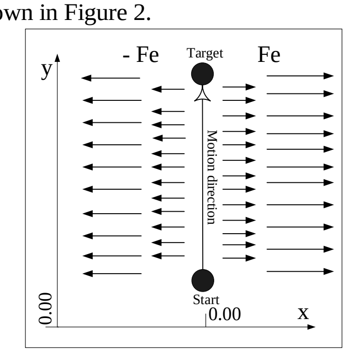

Figure 2: The unstable divergent force field (DF). The field force F_e is a function of position of slave object.

3.1 Experiment for SUSS

As Figure 3 shows, we use Omega3.0 as master hand to manipulate the virtual slave object move slowly from Start to Target, the operational process is exhibit in Figure 3. The data including X and Y position, F_e, et al of slave object and master hand were recorded for every motion. We took 20 times motion then analyzed the data.

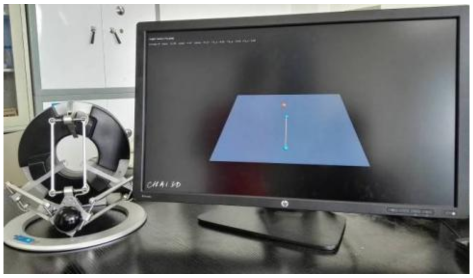

Figure 3: Single user manipulate interface

It can be seen from Figure 4 and Figure 5 that the position errors towards the center line are reduced, which means the master can modify the position errors by adjusting the control force after the dynamic training. But the training result is not as good as the results in [22] because of the influence of time delay. A further analysis about the average absolute errors in X axis direction versus training times is presented in Figure 6 it is not hard to conclude that will decrease along with increasing of the training times. But the times is not the unique factor influencing the positions errors, the time delay and the kind of potential field may be the potential factors for further discussion.

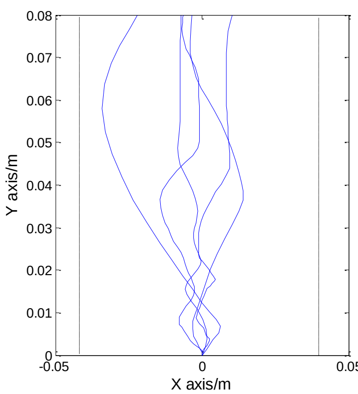

Figure 4: The trajectories of the slave side in first 5 trainings

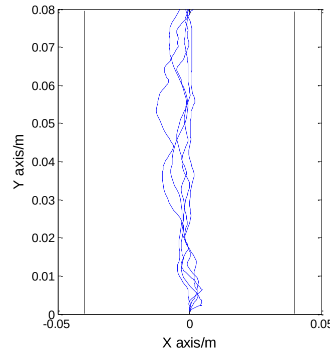

Figure 5: The trajectories of the slave side in last 5 trainings

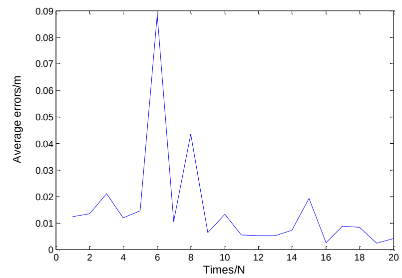

Figure 6: The average errors of X axis direction tend to zero as training times increase

3.2 Experiment for DUSS

As Figure 7 shows, we use Omega3.0 and Phantom as master hands to manipulate the virtual slave object move slowly from Start to Target similarly. For DUSS we set nine groups different α_1, α_2 and α_3,as is shown in Table 1.

Figure 7: Dual-user manipulate interface

Table 1 Value of α_1, α_2 and α_3

Factors / Experiments	α_1	α_2	α_3
1	0.5	0.5	0.5
2	0.5	0.5	0.8
3	0.5	0.5	1
4	0.8	0.2	0.5
5	0.8	0.2	0.8
6	0.8	0.2	1
7	1	0	0.5
8	1	0	0.8
9	1	0	1

The training experiments can be divided into three parts: group 1 to 3 are the first part with same dominance factors α_1 and α_2, and α_3 is the varying parameter, which represent the training authority transmitted from the trainer to the trainee, so are the group 4 to 6 and group 7 to 9. Considering the structure of novel method with multi-dominance factors, the factors α_1 and α_2 satisfy $\alpha_1 + \alpha_2 = 1$, and the ideal case is $\alpha_1 = 1$ and $\alpha_2 = 0$. The results are presented in Figure 8-Figure 10.

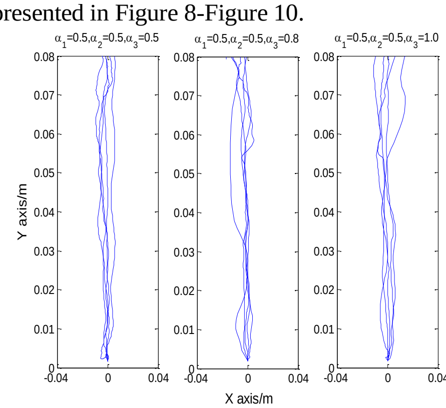

Figure 8: The trajectories of the slave side in group 1to 3

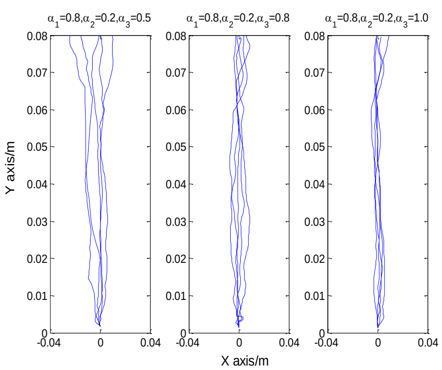

Figure 9: The trajectories of the slave side in group 4 to 6

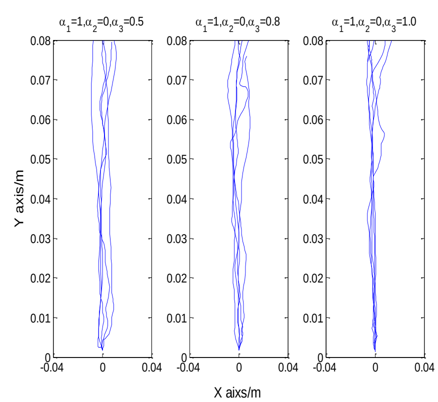

Figure 10: The trajectories of the slave side in group 7 to 9

The left subfigure in Figure 8 shows that with help of the trainer, the fluctuation degree of slave trajectory is not as large as the one in SUSS mode. The training effect is determined by two factors. The first one is the human factor. When the operator interacts with the master for a while, the muscles will remember the force and the control impedance. So we did the experiment separately with a long resting time. The second one is the system structure. When $\alpha_1 = 0.5$ and $\alpha_2 = 0.5$, the action of each master is influenced by both of the slave and the other master with the same authority. The factor α_3 determines the shared degree of the slave. When α_3=1 , the slave is controlled by the master 1, but the actions of master 1 and master 2 are influenced each other. Thus the final training effect is not good. While taking $\alpha_1 = 1$ and $\alpha_2 = 0$, the two masters interact with the slave side directly, thus when $\alpha_3 = 1$, master 1 controls the slave directly, whose effect is same with the SUSS process.

It can be concluded from Figure 8-Figure 10 that the trajectories approach to the ideal path (in Y axis) with larger α_3. It means the manipulation of the slave is transmitted from shared effect of master 1 and master 2 to the single effect of master 2, and the master 2 is trained from a raw beginner to a skillful operator. Different α_1 and α_2 acquire different training effect. Taking larger α_1 and smaller α_2, with better transparency effect, is helpful to the training process with higher precision, which is revealed from the statistics of position errors in Figure 11, though the position errors are smaller when we take α_1=0.5 and α_2=0.5 .

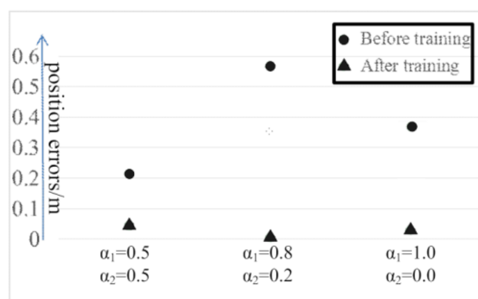

Figure 11: The position errors versus α_1 and α_2

4 CONCLUSION

This paper applies the dual-user shared control architecture for training operators in teleoperation. We examined the operation processes of single user and dual-user shared teleoperation in unstable environment, and discussed the changes of operation force. The difference between teleoperation and directly training through device was analyzed in SUSS experiment. Additionally, the main factors affecting the operation precision were discussed. In DUSS experiment, we focused on how several groups of multi-dominance factors affect the precision and stability in control. The results show when choosing $\alpha_1 = 1 \ \alpha_2 = 0$, which means dual-user manipulates the slave object directly, the training effect and precision performing best. Though compared with single user operation, dual-user operation gets less motion errors. We are still not very sure the efficiency of dual-user training according to current results. It's worth going further in the following studies.

Acknowledgement

This research is sponsored by the National Natural Science Foundation of China (Grant No: 11272256, 61005062 and 60805034) and The Fundamental Research Funds for the Central Universities (Grant No. 3102015BJ006).

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