How can human motion prediction increase transparency?

Nathanaël Jarrassé, Viviane Pasqui and Guillaume Morel

***Abstract*—A major issue in the field of human-robot interaction for assistance to manipulation is *transparency*. This basic feature qualifies the capacity for a robot to follow human movements without any human-perceptible resistive forces.**
In this paper we address the issue of human motion prediction in order to increase the transparency of a robotic manipulator. Our aim is not to predict the motion by itself, but to study how this prediction can be used to improve the robot transparency.
For this purpose, we have designed a setup for performing basic planar manipulation tasks involving movements that are demanded to the subject and thus easily predictible. Moreover, we have developed a general controller which takes a predicted trajectory (recorded from offline free motion experiments) as an input and feeds the robot motors with a weighted sum of three controllers: torque feedforward, variable stiffness control and force feedback control.
Subjects were then asked to perform a task, with or without the assistance of the robot (which was not visible to the subject), and with several sets of gains for the controller tuning. Preliminary results seems to indicate that when a predictive controller with open loop torque feedforward is used, the robot presence is less sensed. Therefore, the transparency is increased.

***Index Terms*—Interactive robotics, transparency, position/force control.**

I. Introduction

In various new applications of interactive robotics, which range from haptics to force-feedback telemanipuation, from fine surgical gesture assistance to rehabilitation, a robotic device and a human being simultaneously manipulate a same object. In most of these applications, the robot is programmed to exert forces and/or to follow a trajectory with the aim of helping the subject to perform a manipulation task.

One of the performance indexes that quantify the robot ability to precisely produce a programmed assistance to the subject is its *transparency*. This may seem contradictory, since transparency measures the robot ability of not applying any assistance. In fact, transparency is a good indicator for force precision since any failure to reach transparency during a zero-resistance experiment will be reproduced and act as a bias is a non-zero force experiment.

A first tremendous effort that was put over years in achieving transparency is mechanical design of haptic devices. In this domain, a particular care shall be put in reducing joint friction and end-effector inertia, which is usually antagonistic with the ability of producing large forces. Achieving transparency for an assisting device of upper limb movements requires several specifications: an important workspace without singularities, a complete reversibility and a low inertia as well as force feedback capacities and stiffness [1]. Moreover, the stability needed for this kind of robots, manipulated by humans, limits the controller stiffness [2]. Recently, new design technologies were developed, which greatly enhance transparency, like those developed by the CEA (French center for atomic energy) for nuclear remote controlled manipulators. They indeed created a new kind of actuator using, among other things, ball screw and cable transmission for a large reduction ratio and a good reversibility. Such technology can be used in different applications fields, like rehabilitation arm orthosis [3]. Another recent example of highly transparent device is the McGill University Pantograph [4]. Here, transparency is achieved in a limited workspace and along a reduced number of degrees of freedom, thanks to a planar parallel mechanical structure.

In any cases, friction and inertia, which are unavoidable, limit the overall system bandwidth and its transparency. Therefore, real time active control has been studied over years as a mean of overcoming these limits.

Including a force sensor and implementing force feedback control is the most popular solution to this problem. The force sensor shall be mounted at the precise place where transparency is needed, usually between the wrist and the end effector for a serial manipulator. Force feedback control allows to cancel quite easily the static joint friction phenomenon. However, it suffers from several limitations : stability, drift, bandwidth limitations. In addition to discrete control problems and sensor noise, dynamics between actuators and force sensors drastically limits force controller performances [2]. Bandwidth limitations are the major problem of these controllers [5], which, in turn address the antagonisms of the design such as rigidity vs inertia and friction.

Several recent papers point out an evolution and a renewal of the way to tackle the human-robot interaction problems. Buerger and Hogan [6] suggest a new approach to improve performance and stability of robot controllers based on force feedback. By studying differences with classical servo control problems, they introduce new control design tools dedicated to the human interaction problem. Using information about the environment dynamics so that to transform coupled stability problem in a robust stability one leads to a more performing controller.

On another hand, in the aim of overcoming force control bandwidth limitations, a new approach is appearing based on predictions of the subject intended movement. The well known control principle is to overcome the force closed loop precision in spite of bandwidth limitations thanks to feedforward.

A major topic in this domain is to predict human movement. Several invariant characteristics in human movement exist along with a few movement laws, especially dedicated to

The authors are with the Univsersity of Paris6-UPMC, Insitut des Systèmes Intelligents et de Robotique (CNRS - FRE 2507). Email: {jarrasse,pasqui,morel}@robot.jussieu.fr.

the upper limb: bell-shaped speed profile [7] (which is linked to the well known minimum jerk criterion [8]), linear synergy between joints [9], isochrony (relation between trajectory length and movement speed), Fitts law (describing the speed/accuracy compromise) or the power law (relation between speed and trajectory curvature) [10]. All these laws may be used to reconstitute in real time the characteristics of a movement. Typically, one can predict the end of the movement from very little information retrieved from sensors at the beginning of a movement. For a simple point-to-point movement, the knowledge of the trajectory beginning is almost enough to reconstitute the whole trajectory with the minimum jerk criterion [11]. Other technical means could be also used to predict human arm movement : Saccadic eye movements or gaze tracking can help detecting movement initiation [12] and predicting the future movement [13]. Human-robot cooperation in an assembly task based on human intention interpretation from gaze movement has been recently tested [14]. Thanks to neural networks, electromyograms (EMG) signals were successfully used to predict arm movement along with arm forces[15] or to control in a predictive way an exoskeleton leg orthosis [16].

Assuming that a motion prediction can be done with enough precision, cooperative robot control can definitely benefit from this information. Corteville and al [11] developed a robot assistant for fast point-to-point movement inspired by human. Their one DOF robot reacts to human forces imposed on a handle (thanks to an admittance controller), and is capable of identifying the motion to move along with the operator, in order to make the movement more comfortable and natural to the subject. This method proves that active participation of the robot based on a model of human movement is advantageous. However, the use of an admittance controller as the lowest level of the controller architecture does not seem to be pertinent. Indeed, the benefits of the force loop and human movement prediction are badly impacted by the drastically low bandwidth of the inner position loop. Therefore, the overall transparency is limited , involving large forces at the human-machine interaction port. Duchaine and Gosselin [17] have recently developed a very similar controller with the capacity of understanding human intention thanks to a force sensor. A low level velocity controller, judged more human friendly, is exploited instead of a position controller. The approach is based on an online variable impedance control. During the comanipulation task, the controller impedance is permanently adapted to the subject movement, according to the time derivative of the force. The experimental validation was made on a drawing task with a parallel manipulator and brings evidences of the transparency increase.

The general idea developed in this paper is to exploit a high bandwidth low level controller in combination with a feedforward compensator based on a human motion prediction. It takes the form of a controller combining a joint position compensator, a feedforward trajectory tracking, and a direct force feedback term, see Section II. An experimental platform was then set up to evaluate this controller. Recall that our aim is not to predict movement, but to understand how to use this prediction at the control level. This is why a specific experimental protocol was set up (see Section III: first, we record several movements of a subject repeatedly realizing a free(without robot) 2DOF reaching task; an averaged set of data extracted from the free reaching tasks is then used as a prediction during the transparency experiment. The transparency experiments consist for a given human subject in repeating the same movement while being attached to a robot, while several combinations of the three control strategies (reaction, prediction and force) are used. Meanwhile, transparency is evaluated (i.e. the force magnitude is measured) and subject feelings are monitored. The experimental results obtained with a limited number of subjects are presented and compared in Section IV. Finally we discuss about the impact of introducing human motion prediction into transparency control and about the further experiment that need to be done to indorse and generalize these first results, see Section IV.

II. Human motion prediction-based transparency control

In this section we derive a general control structure aimed at increasing the transparency of a robotic device held by a human being based on a prediction of the subject's movement. It is assumed that a prediction is available, which takes the form of a robot joint trajectory, $\mathbf{q}_d(t)$. The initial date of the movement, t_0, is also supposed to be known. The really intended motion of the operator, parameterized in the joint space is denoted $\mathbf{q}_r(t)$. It is the motion that the subject would produce without any robot connected to his/her hand. A perfect prediction is thus characterized by $\mathbf{q}_d(t) \equiv \mathbf{q}_r(t)$.

Furthermore, the robotic device is supposed to be governed by the following dynamical equation :

$$\Gamma_m + \mathbf{J}^{\mathrm{T}}(\mathbf{q})\mathbf{F}_{ext} = \mathbf{H}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{b}(\mathbf{q},\dot{\mathbf{q}}) + \mathbf{g}(\mathbf{q}) + \Gamma_f \quad , \qquad (1)$$

where Γ_m is the motor torque resulting from the current, $\mathbf{J}(\mathbf{q})$ is the robot jacobian matrix describing the kinematic mapping from the joint space to the end-effector space, $\mathbf{F}_{ext}$ is the external wrench applied by the operator, $\mathbf{H}(\mathbf{q})$ is the joint space inertia matrix, $\mathbf{b}(\mathbf{q},\dot{\mathbf{q}})$ regroups the Coriolis and centrifugal effects, $\mathbf{g}(\mathbf{q})$ is the joint torque of gravity, and Γ_f is the joint friction torque.

Several control strategies can be imagined. A first one is trajectory control, for which the robotic device is programmed to precisely follow the desired trajectory $\mathbf{q}_d(t)$, thanks to a joint position compensator $\mathbf{C}_p(s)$:

$$\Gamma_{m,1} = \mathbf{C}_p(s)\left(\mathbf{q}_d(t) - \mathbf{q}(t)\right) \quad . \qquad (2)$$

Note that the compensator may include an estimated dynamical model of the robot, *e.g.* it may realize a dynamical decoupling thanks to a set of estimated parameters $\hat{\mathbf{H}}(\mathbf{q})$, $\hat{\mathbf{g}}(\mathbf{q})$, $\hat{\mathbf{b}}(\mathbf{q},\dot{\mathbf{q}})$, $\hat{\Gamma}_f$. Ultimately, if both the prediction and the robot dynamic positioning precision were perfect, then the robot and the subject would produce the exact same motion (*i.e.* $\mathbf{q}(t) \equiv \mathbf{q}_d(t) \equiv \mathbf{q}_r(t)$). This would result in no dynamic forces at the interface. However, we expect this strategy to be poorly robust with respect to motion prediction errors. Indeed, in order to achieve high precision, it is required that high gains are used. Therefore, if $\mathbf{q}_d(t)$ differs (even slightly) from the real subject intended motion $\mathbf{q}_r(t)$, which seems unavoidable, then large forces will occur at the interface. This controller is still kept as a candidate in order to experimentally evidence this expected phenomenon.

A second strategy that can be implemented is feedforward trajectory tracking:

$$\Gamma_{m,2} = \hat{\Gamma}_m(\mathbf{q}_d, \dot{\mathbf{q}}_d, \ddot{\mathbf{q}}_d) \quad , \tag{3}$$

where $\hat{\Gamma}_m(\mathbf{q}_d, \dot{\mathbf{q}}_d, \ddot{\mathbf{q}}_d)$ is the estimation of the torque that the actuator shall produce in order to follow the desired trajectory. Note that possible realization of the torque feedforward is:

$$\hat{\Gamma}_m(\mathbf{q}_d, \dot{\mathbf{q}}_d, \ddot{\mathbf{q}}_d) = \hat{\mathbf{H}}(\mathbf{q}_d)\ddot{\mathbf{q}}_d + \hat{\mathbf{b}}(\mathbf{q}_d, \dot{\mathbf{q}}_d) + \hat{\mathbf{g}}(\mathbf{q}_d) + \hat{\Gamma}_f \quad . \tag{4}$$

Again, with a perfect prediction and a perfect torque estimation, one gets $\mathbf{q}(t) \equiv \mathbf{q}_d(t) \equiv \mathbf{q}_r(t)$. Moreover, with this approach, in contrary to the first strategy, small discrepancy between the predicted and real motions will not produce high forces at the interface. This is why we expect this approach to provide a better feeling of transparency.

The last control strategy that we have implemented is force feedback control, by the use of a joint-level torque compensator $\mathbf{C}_f(s)$:

$$\Gamma_{m,3} = -\mathbf{C}_f(s)\mathbf{J}^{\intercal}(\mathbf{q})\mathbf{F}_{ext} \quad , \tag{5}$$

where $\mathbf{J}^{\intercal}(\mathbf{q})$ is used to map the measured force $\mathbf{F}_{ext}$ into a joint equivalent. Note that this controller does not benefit from any predicted motion, it is only reactive to subject forces. In fact, in the rest of the paper, the controller will be a weighted sum of the three strategies described in Equations (2), (3) and (5):

$$\Gamma_m = \alpha_1\Gamma_{m,1} + \alpha_2\Gamma_{m,2} + \alpha_3\Gamma_{m,3}, \tag{6}$$

where $\alpha_i \in [0,1]$, for $i \in \{1..3\}$. Tuning the parameters α_i is a way of applying the different strategies, alone or in combination.

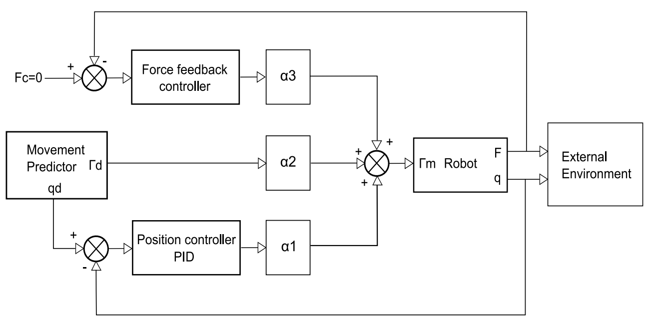

Fig. 1. Three strategies controller

III. EXPERIMENTAL SETUP

Elementary planar manipulation tasks were performed with a specific handle fitted with position and force sensors, which can be used alone or mechanically connected to the end-effector of a 2DOF serial robot manipulator.

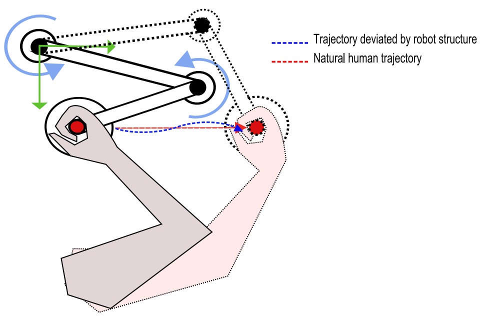

Fig. 2. Simple point-to-point movement

An opaque surface was installed hiding the hand of the subject, so that he/she could not visually determine wether the robot is connected or not to the handle. With this apparatus, the subject attention is focused on this white planar surface, while he/she waits for the start signal given through an LED to reach a target materialized on the surface by a circle. In order to allow the subject to see his/her hand position through the opaque surface placed over the table and the robot, a laser pointer is placed inside the handle and projects a spot on the surface. Starting and ending areas are always visible over the opaque surface during all the experiment.

The experiment begins by telling the subject to grab the handle (disconnected from the robot) which is placed under the opaque surface. Then he is instructed to perform five times the same simple point-to-point movement, meanwhile the handle position is recorded. The measures are then averaged and filtered in order to synthesize a movement model of the subject trajectory, later used as a prediction for the transparency experiment.

The transparency experiment consists in performing the same point to point movement with several controller configurations. The transparency evaluation is made by studying various factors : values of junction between robot and human forces, path analysis and subjects feelings.

After the trajectory recording part, the subject is told to perform the same movement when the red LED turns on. No particular speed indication or way of grasping the handle during the movement were given during the experiments with the aim to study the most natural behavior. The different configurations which have been tested are the following : null current, force feedback control, open loop feedforward, and several combinations, especially force feedback added to feedforward.

A. *Robotic device*

The robot is a two degrees of freedom manipulandum, similar to the MIT-MANUS [18], with two parallel rotations. This kind of kinematic configuration allows us to ease the control while enabling, unlike a single-dimensional system, unconstrained natural human movement during a co-manipulation task. The handle orientation is left free thanks to the use of low friction ball bearings. The system is actuated by two 90 watts Maxon DC gearhead motors. The first axis uses an 1:20.25 gearhead ratio delivering up to 800Ncm and the second one a 1:4.5 gearhead ratio for 120 Ncm. Second axis motion is transferred by a timing belt. The angular motor position is measured by optical incremental encoders. The handle is mounted on the end effector extremity. Between the handle and the effector, a force sensor is installed in order to measure the force exerted by the subject on the handle. This measured force is used to compute the force control part of our controller.
The 6-axis force/torque(F/T) sensor is a Nano43 Transducer from ATI Industrial Automation allowing us to reconstruct the 3 forces and 3 torques components. For our purpose we are only interested in two of the six components (X and Y force components) and for this component the force range is +/- 36N with a resolution of about 1mN. The controller is equipped with an Analog and Digital I/O PCI card (National Instrument, model 6034E) in which we use six 16 bit A/D channels for acquiring the readings of the force sensor.

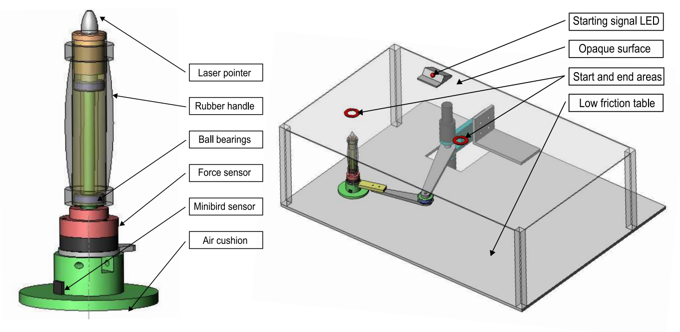

Fig. 3. 3D view of the handle and of the experimental setup

The handle is also fitted with a magnetic position and orientation sensor, a measurement MINIBIRD system from Ascension Technology Corporation, which is installed under the force sensor (the magnetic emitter of the system is placed under the table). It permits to measure the position and orientation at a 100Hz frequency and compute speed of the handle during the experiments, and it especially allows the controller to learn movement characteristics of the subject during the pre-experimental part. As the experiment deals with low level-forces, a particular attention has been given to minimize friction. This is why the lowest part of the handle was designed with an air cushion system, in the purpose of reducing friction between the handle and the table, even if the subject strongly pushes against the sliding surface.
The robot controller architecture is based on a PC104 board with an endowed 3 channel axis controller. It runs at 1kHz the control law 6 thanks to a real time operating system (RTlinux).

B. *Trajectory recording*

During the pre-experiments, the subject is asked to perform the same movement from the start area to the end area (marked up over the opaque surface). This is repeated five times in a row. Five attempts are enough to extract general features of the subject movement. In fact healthy subject for a free upper-limb movement performs a quite repeatable motion. Speed and position profiles are approximately constant for a subject and a given movement. Recording five attempts allows us to reach the different values in order to filter little subjects variations or errors, such as minibird data which can be perturbed by magnetic fields. Data is filtered and then interpolated from 100Hz record (maximum data rate of the minibird sensor) to a 1kHz data trajectory compatible with the control loop clock. Another important data is the reaction time of the subject (the time laps needed by a subject to initiate the movement after the visual start signal is turn on). Indeed, the ”anticipation” is done by reinjecting a recorded caracteristical move, so the challenge is to perfectly synchronize the subject movement start with the injection of the recorded move. Indeed if a time-lag appears, large forces will occur at the human-robot interface. The knowledge of that reaction time t_0 allows us to synchronize robot anticipation with the subject move during the evaluations experiments.

C. *Computing* $\hat{\Gamma}_m$

Calculating $\hat{\Gamma}_m$ with equation (4) requires a model identification and will lead to imprecision. We've rather used a simple experimental method which has the double advantage of good precision and no model requirement.
Once the trajectory is available, the robot end-effector extremity is placed on the start area with a standard PID position controller (see Eq. 2). Then the recorded interpolated average trajectory is fed to the robot controller. During the robot movement, the motor currents are recorded. In fact, during this experiment, the position control loop calculates the necessary torques to apply to actuators to move the robot structure along the human subject trajectory. The resulting output is $\hat{\Gamma}_m$, which will be used as an open-loop feedforwrd signal to realize the prediction feature of the controller.

IV. Results of transparency tests

During the experiments we used a PID for the position controller, and a simple proportionnal term for the force compensator. Several combinations of the three control law were tested. With a same subject, we evaluated interaction force on the handle for a simple point-to-point movement with:

- null current, for a reference - strategy 0
- joint position compensator of Eq. (2) - stategy 1
- feedforward trajectory tracking (3) - stategy 2
- force feedback control (5) - strategy 3
- force feedback control with feedforward trajectory tracking (5)+(3) - strategy 4

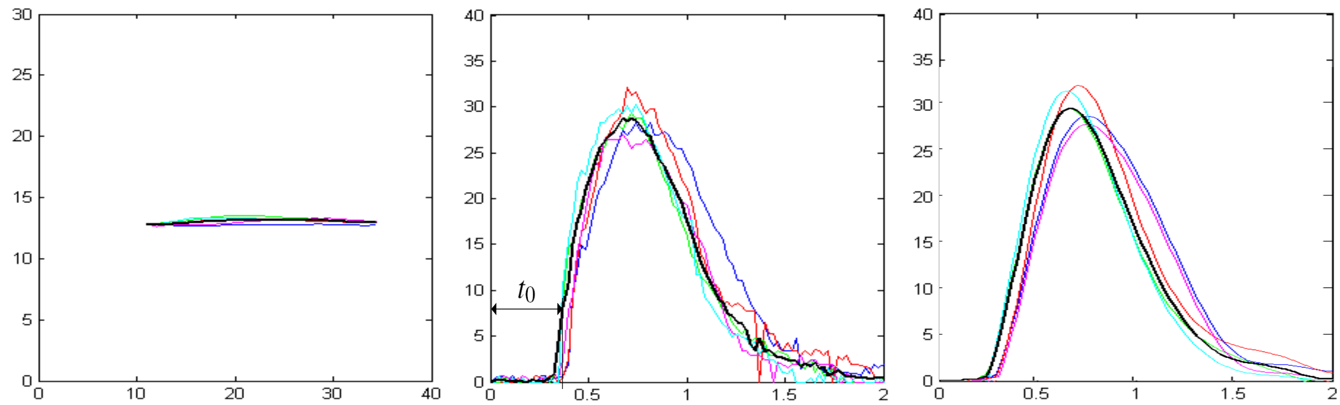

Fig. 4. Graphics of positions and speeds recording for the same simple point-to-point movement and average trajectory

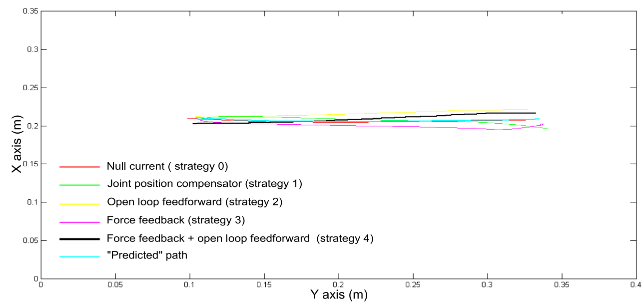

Fig. 5. Hand position during the experiments with the different controllers

We analyzed hand geometrical paths and average forces applied through the handle to quantitatively evaluate the different controllers.

Figure 5 shows the different geometrical path obtained for one subject performing one task. It can be observed that the final position significantly varies during the experiments, which can be explained by the lack of precision asked to the subject: his goal was to bring a small laser spot into a approx. 3cm diameter circle. Since the different controllers appear not to consistently impact hand path, we mostly focused on mesured forces appearing on the handle, that are compared for the five different strategies in Figure 6.

Strategy 1 limits the force (as compared to the non compensation experiment) at the beginning of the motion. However, it quickly perturbs the subject and the little desynchronization between real move and predicted one lead to a lack of transparency during the rest of the move. The influence of the synchornization is emphasized in Fig. 7.

A qualitative approach was also used to evaluate controllers performances, by asking subject about his feelings. Coherently, the strategy 1 was badly appreaciated by the subject owing to the impress of being completely directed, and not free to speed up or slow down.

The strategy 2 (feedforward trajectory tracking) produced better results, especially at the move initiation, and allowed a great interaction force decrease specially during the second

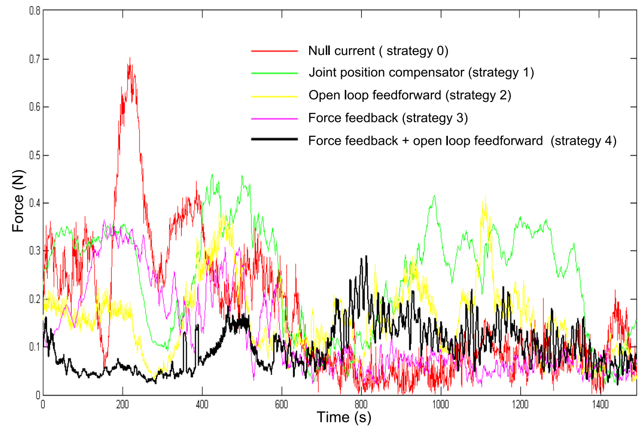

Fig. 6. Average of mesured efforts at the interface during point-to-point movement for the differents controllers

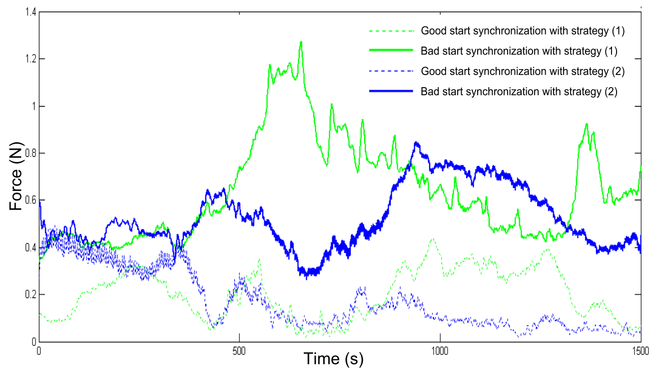

Fig. 7. Average of mesured efforts at the interface for a synchronized and not synchronized movemenent with strategy 1 (position compensator) and strategy 2 (predictor)

phase of the motion, where the lack of rigidity allows small forces (see the yellow plot in Figure 6). Subjects appeared to feel really more free and appreciated the controller effects and the ”disparition” of the robot dynamic.

The third strategy (force feedback control) also provided good force minimization. Contrary to previous strategies, subjects were not perturbed by desynchronization problems since no prediction was used. The force level, once the transcient response is finished, is very low. However, during the initial phase of the movement, the limited bandwidth of force feedback doesn't allow the controller to react as quickly as the prediction strategy can.

That's why the combination of force feedback and feedforward trajectory tracking controllers (stratgey 4, black plot) gave the best results during our experiments.

Combination of 2 and 3 finally results in a force feedback controller with less bandwidth limitations, and so which is capable of minimizing forces during great forces variations like the movement initiations. Qualitatively speaking, this combination really seemed to greatly reduce subject sensation of being interacting with a robot. Problems of critical phase of movement initiation, when traditionnally possible external presence can be sharply detected (with friction and particulary inertia phenomenon), seem to be solved in part.

V. Conclusion

This early work provides new evidences that human motion prediction could allow controllers to achieve a better transparency than purely reactive strategies. This is consistent with several published studies mentionned in the introduction, such as [11]. However we notably worked on a simple movement, and our experimental results are not fully consistent statistically speaking owing to the small number of subject. Furthermore, the low-level forces we work with are close to sliding friction between the handle and the plane, and we are now developing a higher quality experimental setup to verify the first conclusions of the present study.

Nevertheless, quite interesting clues can be extracted from the current results. The feedforward trajectory tracking seems really competitive in terms of transparency, with a real efficiency at the beginning of the move. This is consistent with Corteville note [11] about the segmentation of a point to point movement into several phases. Our results seem to indicate that the controller could split the strategy along a trajectory in three parts:

1) The beginning of the motion requires large forces to initiate movement (to accelerate the entire robot structure and to overcome dry friction), that's why the combinaison of the force feedback control and feedforward trajectory tracking is the best combination.
2) In the middle of the trajectory, very little forces are needed, human haptic sensibility is thus enhanced. Even a little desynchronization between the applied anticipation and the real movement may be disturbing. Moreover, the acceleration is small which limits the force error due to the bandwitdh limitation. That's why during this second phase, the force feedback is enough to maximize transparency at the interface.
3) At the end of the move, even if the force feedback appears more performant in terms of force, the anticipation is said as very helpful by the subjects. We would suggest to keep it in this final phase.

In summary, rather than the use of two fixed coefficient α_i, the solution allowing the best transparency feeling could be the use of two time dependant variables $\alpha_i(t)$ in order to allow a maximization of the predictive strategy at the beginning and end, and a minimization of it effects during the rest of the movements.

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