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Modelling of human haptic skill: a framework and preliminary results

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Abstract: Haptic interaction in human motor tasks requires special modelling techniques in robot learning. This paper proposes a novel scheme for haptic skill modelling, covering the modelling procedure starting from reference data acquisition until a competent model is obtained. The iterative structure of the proposed scheme provides a clear guideline to the modelling workflow. The scheme as well as the distinct features of haptic skill modelling are discussed and illustrated by modelling social handshake dynamics.

1. INTRODUCTION

Researchers have developed various methods in the past decades to let robots learn human skills. Works published so far are task specific with usually distinct workflows. Apart from the common learning methods for some cases such as reinforcement learning and programming by demonstration, a systematic description of the process is yet to be proposed. This paper, after denoting haptic skill as motor skill with force interaction, argues that for haptic skill modelling, a specific area of human skill modelling, there are common issues. A framework is proposed as a guideline for related work.

As an example, the modelling of social handshaking is used to discuss the proposed scheme in detail. Handshake contains the typical problems for haptic skill modelling while being simple enough for implementation on robots. It is shown that following the design loop of the scheme, each of the modelling iterations shows certain problems. The information is fed back to the very beginning of the loop and a next iteration is carried out with a remedy implemented to the system, so that each iteration yields improved results.

The paper is structured as follows. In Section 2, the challenges of haptic skill modelling are discussed, with a novel scheme of haptic skill modelling proposed. In Section 3, the modelling of handshakes is discussed as an example of employing the proposed scheme, followed by the performance evaluation and discussions in Section 4. Conclusions are drawn in Section 5.

2. A NOVEL SCHEME FOR HUMAN HAPTIC SKILL MODELLING

In this section, first the distinction of haptic skill in comparison with other motor skills is emphasized. Then a brief overview of the limited number of related works on haptic skill modelling is given, based on which a novel scheme of human haptic skill modelling is proposed and discussed in the end.

2.1 Haptic skill

Humans reason in a symbolic level, leaving a gap between the symbolic commands and the muscle groups that work in a rather low level to make the actions, see Wolpert and Ghahramani (2000). The skills that humans accumulate to fulfill this gap are often referred to as *motor skills*. Most motor skills are kinaesthetic behaviours with little or simple contact forces involved such as walking, arm reaching, etc.

The term *haptic skill* is used here to denote a sub class of motor skills with emphasized haptic interactions. Although haptics consists both tactual and kinaethetic factors, in this paper only the kinaethetic interaction is concerned. Examples of haptic skill include: ping-pong playing, hammering, violin playing, bottle opening, handshaking, dancing, etc.

According to the objectives of the task, haptic skill can be further divided into two categories: goal oriented and process oriented.

Goal oriented haptic skill requires the achievement of certain termination criteria. Examples of such skill are ping-pong playing, bottle opening, and hammering. The dynamics of the process by which the manipulator achieves the goal is often irrelevant to task completion but affects evaluation criteria such as completion speed or safety.

Process oriented haptic skill puts additional requirements on the dynamic process before a final goal is reached. For instance, in violin playing the bowing force and motion must be carefully coordinated to yield the expected timbres; during handshaking, the force perceived by the partner must follow certain patterns in order to make him feel comfort. Some skills in this category do not necessarily have a final goal to achieve, with the performance measure purely based on the dynamics of the process.

Modelling of process oriented haptic skill differs from the motor skills modelling methods, as it concerns with haptic interactions, most importantly, force dynamics, see Peters and Schaal (2006). For example, in the case of handshake

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modelling, the feeling of realistic serves as a primary objective to the performance measure. However, in this problem, neither the model of the human behaviour nor the criteria of human definition of a realistic handshake is clear. The coupling of force and position signals between partners also increases the difficulty of modelling.

2.2 Related works

From the above analysis it can be expected that the requirement on force dynamics increases the difficulty of haptic skill modelling. There have been individual studies reported on modelling specific human haptic skill and transferring them to robots. Acosta et al. (2003) and Andersson (1989) reported teaching specialized robots to play ping pong, while general robot manipulators are taught to carry out tasks such as hammering by Arsenio (2004) and bottle opening by Fukano et al. (2004). However, the above tasks all belong to goal oriented haptic skill. For process oriented haptic skill, very limited publications can be found. Kunii and Hashimoto (1995) created handshake using a simple 1-degree-of-freedom device, but the device is tele-operated with little modelling involved.

Although the above works resulted in technical systems that imitate human skills, the main concern lies in the development of the device rather than the modelling procedures. The hardware device is often developed before modelling the skill. In this approach, the following research is limited by hardware constraints. When a better technology can be offered to the implementation, the workflow has to be repeated. For example, when modelling the skill of Ping-pong playing, Andersson (1989) and Acosta et al. (2003) developed different devices while also carrying out two different approaches of modelling. However, it is argued in this paper that the modelling and analysis should not be bounded by hardware constraints; the improvement of hardware can result in a better representation of the modelling results, while leaving the major part of the modelling work unaffected.

2.3 A novel scheme for haptic skill modelling

A modelling scheme is proposed as shown in Fig. 1 addressing the common issues of haptic modelling. The aim of proposing the scheme is not to suggest any novel modelling methodology but to provide a starting point for discussions, so that the issues of this new research area can be more specifically studied and a perspicuous overview can be drawn on the progresses of different fields.

Each block in the scheme is discussed more in detail below, together with the evaluation and termination criteria.

A priori knowledge Although automated programming of robots is an active research issue, the learning environment needs to be well defined by experts. At the current stage a priori knowledge is necessary in designing experiments to measure human performance, selecting the initial model and hence the parameter identification method. After each of the modelling iterations the knowledge of the expert is updated by new information from the iteration.

Human performance measurement This is the main argument of this novel scheme. Different from other mod-

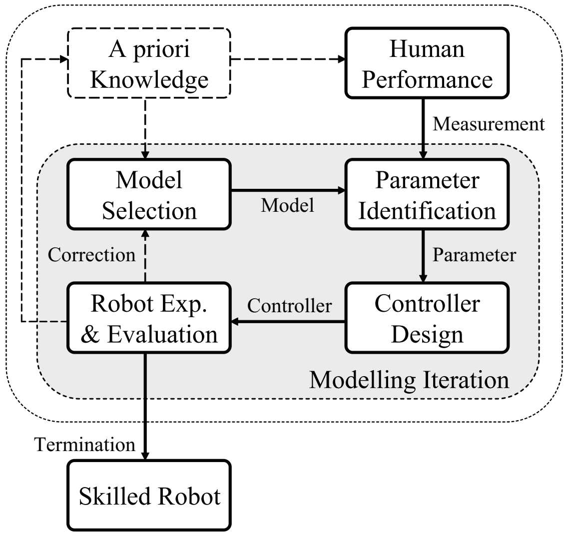


Fig. 1. A novel scheme of haptic skill modelling. Solid lines denote signals and data flows while dashed lines denote knowledge flows

elling tasks, human haptic skill modelling often requires human performance measurements, both as a reference for analysis and as an evaluation guideline. It is particularly important for process oriented haptic skill, as the process in concern needs a reference from human performance. It is also important that human performance measurement is taken *before* and *independently* from the engineering of technical systems used to implement the skill later on, although the design of the experiments for measuring needs to be guided by the a priori knowledge. By this approach the original information about human performance can be acquired, although subject to the means of measuring, without being distorted by implementation constraints.

Modelling iteration The grey dashed box in Fig. 1 illustrates the modelling iteration, which consists of model selection, parameter identification, controller design, and robot experiment with evaluation. The model is not specified by the scheme, it can vary from deterministic to stochastic or even hierarchical. After a model is selected, human performance measurements are used to estimate the parameters to the model. Robot controllers are then designed and implemented. Technical constraints of implementation apply in this phase. However, with the previous parts of the modelling being unbounded, future improvement of the technologies can be implemented yielding a better representation of the skill while keeping the modelling results unchanged.

Evaluation criteria Generic evaluation standards are yet to be set. Discussions are taking place on the evaluation of human performance, where in some cases there are quantitative measures such as task completion time, while others being more subjective. After the evaluation, the current modelling iteration is over, the knowledge of the expert is updated with the newest findings and problems, and corrections are made to the model selection or any necessary block thereafter.

Termination criteria The termination policy of modelling is task specific. The various factors that affect human performance suggest the possible necessity of borrowing findings from other disciplines. In general when the performance of the robot is within the acceptable range and after iterations the objective does not improve significantly, the modelling can be terminated with a skilled robot.

For discussion convenience, the modelling of human handshaking is taken as an example to demonstrate the details of the proposed scheme in the next section. The robot and the human are modelled to be two dynamical systems coupled together with force and position exchanges. A second order mechanical impedance model is used to represent the dynamical behaviour of the human arm. A model of the same structure but with different parameters is used to control the robot. In modelling practice, as shown in the next section, the proposed scheme gives a clear guideline of workflow. The measured human performance plays an important role in the modelling iterations. Besides, the changes made to certain blocks of the scheme benefit from the unchanged results from the other blocks from the previous iterations.

3. MODELLING OF HUMAN HANDSHAKE: AN EXAMPLE

This section, together with the following one, aims to discuss in detail the implementation of the proposed scheme in practice. Modelling of handshake is taken as an example. Three iterations are carried out, each yielding improved results. This section illustrates the methodology and the workflow of each iteration, while the next section focuses on the results and the performance evaluations. The remainder of this chapter describes the procedure of modelling the arm dynamics of handshaking following the proposed scheme. An outline is given as follows:

- A pilot study is carried out to gather first knowledge about the handshake dynamics.
- In the first iteration, a large amount of human handshakes are measured. The handshake process is segmented and a switching controller model is used.
- In the second iteration, desired trajectories are generated by a planner with a motion synthesis modular. Trajectory playback is realized on the robot.
- In the third iteration, new control methods are employed to achieve compliance on the robot. Realistic handshake is achieved with passive human partners.

Due to the size limitation, this paper is concentrated in showing the logical workflow and the results and evaluations. The technical details are omitted when standard methods are used. References are given for non-standard methods for concerned readers. For comparison convenience, the results are covered in the next section.

3.1 Pilot study

The starting point in the proposed scheme is gathering a priori knowledge. Since very few reports can be found in mimicking or recreating handshake dynamics, a pre-study experiment is necessary to get close to the problems. 300 handshakes are performed by volunteered male college students. The exchanged force is recorded using a haptic data glove, the TSG-1 as in Wang et al. (2007), and the motion is recorded using a video camera. In spite of the awareness of technical limitations, the following findings are made from the pre-study experiments:

- Handshake is a dynamic process with intra- and inter- subject uncertainties. The pattern which helps a person to distinguish a realistic handshake from a fake one is yet to be identified. The actual motion trajectory is affected by the exerted force dynamics from both sides of the handshake pair.
- A typical handshake can be divided into three stages: approach, shake, and release. The switching conditions are the contact and lose of contact between the two hands of the participants.
- The shaking stage of handshake consists of both force and position exchanges, while the other two stages involve only free space motion.

The first knowledge of handshake is used to guide the design and modelling of the first iteration.

3.2 The first modelling iteration

With a priori knowledge from the pilot study, the next step to start the first iteration is to measure the human performance data. Considering the results from the pilot experiment, a larger number of handshake performances between two human participants are recorded. Following the argument of this paper, this is carried out regardless of the robotic device to which the modelled handshake is implemented. The only a prior information used in the measurement is, that since haptic is concerned, force and motion dynamics are measured. As arm motion is mainly concerned, optical markers are placed on the shoulder, elbow, as well as the back of the hand of both participants during each experiment. The haptic gloves used are TSG-2, with improved performance in measuring interaction forces during handshaking, technical details as in Wang et al. (2007).

A total number of 900 handshakes are recorded from 24 male college students (mean age 28, standard deviation 2.292). As the aim of modelling is to teach a robot to shake hands which feels realistic to an arbitrary human counterpart, the participants are not given any instruction on how they should conduct the handshake to achieve natural behaviours.

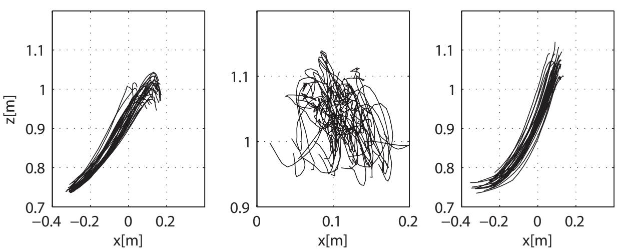


Fig. 2. Segmented hand trajectory in 30 recorded handshakes in longitude(x)-vertical(z) plane. Left to right: Approaching, shaking, retreating stages

The handshake process is segmented according to the control methods in the robot which will be discussed later in this section. The optical tracking system used in the experiment provides 3-dimensional measurements of the trajectories of handshake dynamics. In Fig. 2, segmented trajectories are shown in longitude-vertical plane. The lateral motion is small comparing with the other two axes and is therefore neglected.

Inter-trial similarities can be observed for the trajectories of reaching and retreating stages, while the shaking stage curves differ significantly. However, if the vertical motion is plotted against time as shown in Fig. 3, similar pattern can be observed for different trial of handshakes.

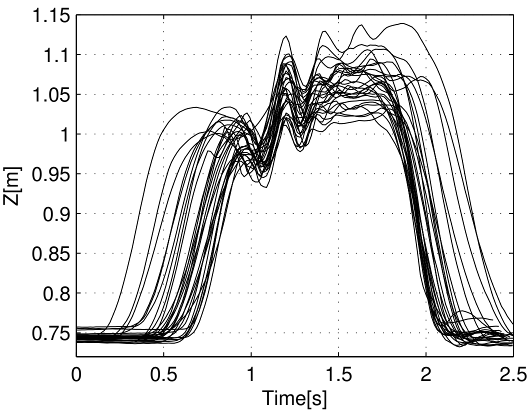


Fig. 3. Trajectories of 30 handshakes (3 stages). Vertical motion against time

The human-robot system when in contact is modelled as two dynamical systems coupled together by force and position exchanges, as shown in Fig. 4. Without contact, the robot has no interaction with the human and thus conducts free space motion.

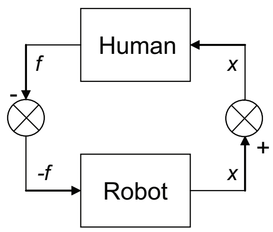


Fig. 4. Coupled system of robot and human with force and position exchanges

A three state switching model is therefore constructed corresponding to the approaching, shaking, and retreating stages. The similar patterns of approaching and retreating stages support the hypothesis of modelling the two as free space motion following desired trajectories. For the shaking stage, the hypothesis is that it can be represented by the response of a second order linear time-invariant (LTI) system to certain inputs. As for the handshake, the arm can be regarded as being driven by the combined force from both partners. The human arm dynamics can be represented as the following impedance model:

$$F = M\ddot{x} + D\dot{x} + K(x - x_0), \tag{1}$$

where F stands for interaction force, x for displacement, x_0 for the equilibrium position, M, D, and K corresponds to the representative mass, damping, and stiffness parameters, respectively. The LTI model is well studied in control theory, therefore standard methods can be applied for stability and performance analysis. Parameter estimation is also convenient with the LTI model. The 900 handshakes recorded are analyzed using standard least squares method to estimate parameters for the impedance model.

However, as the measured force is the combined force of both partners, without knowing the desired trajectory within each block in Fig. 4, the estimated parameters are for the coupled system rather than for each partner. Therefore the results cannot be implemented onto the robot. The iteration thus ends at this point, with correction information on the model selection.

3.3 The second modelling iteration

The second iteration starts with updating the a priori knowledge with the information from the first iteration. As there is no available method to measure the decoupled interaction force at the contact point of each partner, the simple impedance model with estimated parameters is not capable for the modelling and is changed.

The human performance results are inherited from last iteration. The model selection is changed, however. The robot is firstly modelled as a second order LTI system, leaving the human part for later iterations. The only assumption made on the human side is that the human conducts a passive behaviour as defined in Colgate (1988), so that stability of the coupled system can be assured.

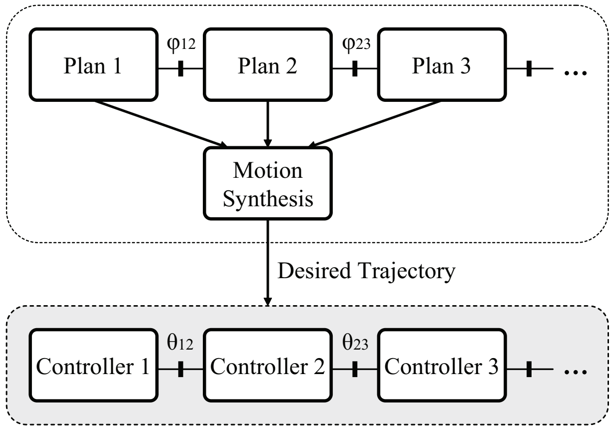


Fig. 5. The model structure for handshake dynamics. The motion initiatives generated from the Plan blocks are synthesized in the Motion Synthesis block into a coherent trajectory and sent to appropriate controllers to actuate the robot. θ and ϕ stand for the transition conditions

For controller design, as shown in Fig. 5, a switching model with motion synthesis is used to generate a planned trajectory, which serves as the reference signal to a controller to be implemented onto the robot. The method proposed in Asarin et al. (2000) is employed to ensure smooth position, velocity, and acceleration.

The robot is controlled with standard position control. The desired trajectory is taken from the planner. The force feedback from the human partner is ignored in this controller model.

The resulting model is implemented onto a 10-degrees-of-freedom robot arm. The robot can perform handshakes following the generated desire trajectories. However, since force signals are not considered in the position controller, the robot arm cannot produce compliance and a completely stiff handshake is not realistic. The second iteration is terminated with corrections on the controller design.

3.4 The third modelling iteration

In the third iteration, while keeping the switch model structure, improvements are made to the shaking stage. The main aim of the iteration is to introduce compliance into the robot controller.

However, human performance measurements have to be revisited in this iteration. As impedance control with desired trajectories is used to realize compliance control of the robot, human dynamical model is also needed. Therefore an excitation signal with a maximum amplitude of $10cm$ consisting of mixed frequency components ranging $0 - 25Hz$ is exerted onto a human participant. The participant is required to maintain passive to the excitation signal, while the position dynamics is measured during the process. With the measured data, parameter estimation can be carried out. Averaging repeated trials of the same participant gives the impedance parameters of the specific participant when trying to be passive.

For controller design, force based impedance control is employed as shown in Fig. 6. The human model employs the estimated parameters of the new human performance measurements. The motion trajectory is recorded of the same participant shaking hand with a leading human partner. Interaction force is estimated with the impedance model and serves as a plan in the robot test with the same person trying to maintain a similar arm performance.

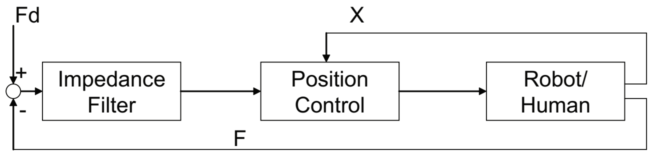


Fig. 6. Controller structure in the shaking stage. F_d the desired force, F the actual interaction force

In robot-human tests, the resulted model is able to carry out realistic handshakes while the human partner stays passive. The third iteration therefore terminates. Corrections for the next iteration are to relax the assumption on passive human behaviour. This will be discussed in the future work in Section 5.

4. RESULTS AND PERFORMANCE EVALUATIONS

In the first iteration, the model is not well chosen, such that no robotic experiment results can be obtained.

In the second iteration, stable handshake between robot and human is achieved. The position controlled robot does not respond to human exerted forces, but it can render generated desired trajectories to the human accurately. As shown in Fig. 7.

In the third iteration, after introducing compliance, the robot handshake feels realistic to human participants.

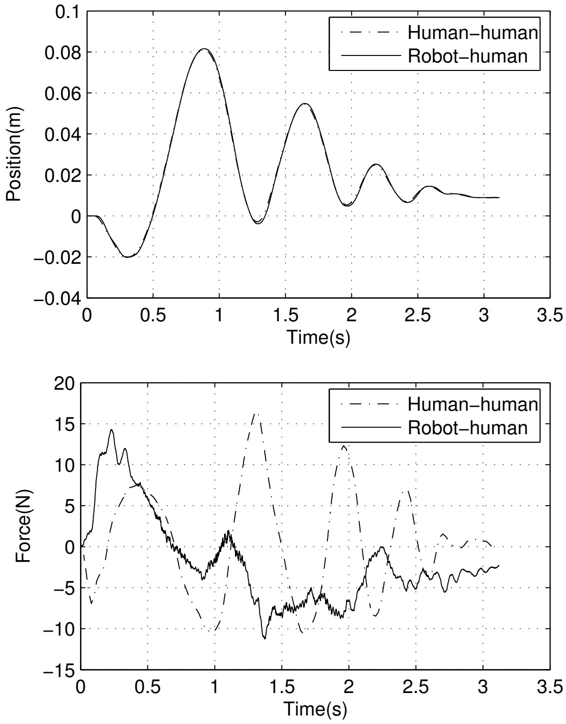


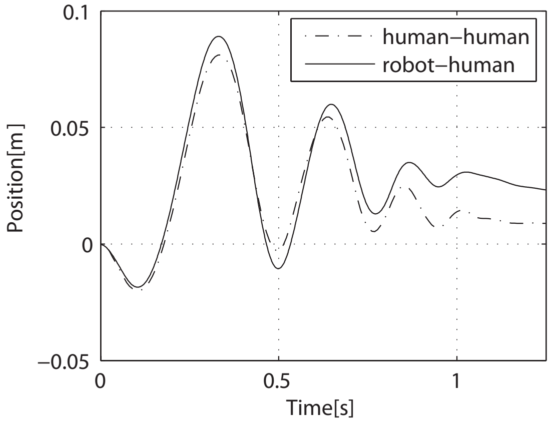
Fig. 7. Comparison of robot experiment results with human performance. Position control. a(upper): position; b(lower): force

Recordings show that when the motion is close to the desired trajectory, as shown in Fig. 8a with a root mean square of 0.011m, the interaction force recorded from the force sensor on the robot is very similar with the previous estimation with a root mean square of 3.23N, as in Fig. 8b.

In the experiment, stability is maintained with or without a human participant. When no hand holds onto the robot arm, the resulting trajectory shows a higher amplitude of motion since part of the load is missing hence the actual load is smaller than in the model.

Comparing with the previous two iteration results, the third iteration gives a realistic feeling of handshake provided that the human follows the robot. In human-robot tests, the human subject is asked to handshake firstly with the robot, and then with the human from whom the robot is modeled. Preliminary testers report the feeling of realness, especially comparing with the previous models. However, due to human uncertainties, voluntary forces applied by the human subject result in oscillations in force. The break of realness is reported in these cases. Subjective evaluation tests will be carried out after technical iteration gives promising results.

The performance of the proposed scheme has also been illustrated. It yields results improvements while being efficient in saving the amount of work and make minimum changes. It has been shown in Section 3 and 4 that following the proposed scheme, each iteration is complete with improving results. In addition, the human performance measures in the first iteration benefit also the second one. On the other hand, when the human performance measures are changed in the third iteration, the other parts of the scheme can remain the same.



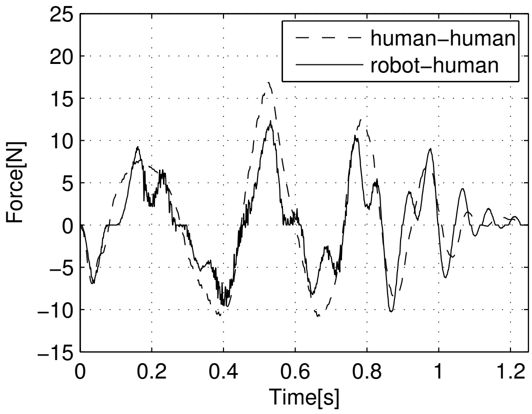


Fig. 8. Comparison of robot experiment results with human performance. Force based impedance control. a(upper): position; b(lower): force

The proposed scheme suits best for process haptic skill modelling, since the dynamics of the haptic interaction is concerned. For other types of skill, the necessity of human performance measurement might be lower, and then the proposed scheme degrades to the standard modelling procedure of model selection, parameter identification, and performance evaluation.

5. CONCLUSIONS AND FUTURE WORK

In this paper, modelling of haptic skill is viewed as a research area with special requirements than conventional modelling tasks because of the necessity of considering the force interaction. A novel scheme of modelling human haptic skill is proposed. Modelling the arm motion dynamics during handshaking is used to demonstrate the scheme. The problem of motion synthesis and force based impedance control are studied. Simulation and robot experiments are carried out to test the results.

It is shown that following the scheme, a switching model prototype with superposed output and force based impedance controller is obtained from the data recorded from well designed experiments. The robot with the model implemented is capable of handshaking realistically with a passive partner in the aspect of arm motion dynamics.

During the modelling procedure, each of the three iterations is complete. They employ different models, different controllers, as well as different evaluation criteria. On the other hand, it is convenient to change a part of the model in this modular based scheme. For the same robotic device, higher accuracy measurements or a better designed controller would lead to better performances; while for the same data set measured in human to human experiments, an improved controller or better estimated parameters would yield better results.

At this stage only vertical axis arm motion is considered in the modelling of handshakes. The robot is modelled based on the assumption of a passive partner. Future iterations will look into these factors.

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