A Bi-level Optimization Approach to Get an Optimal Combination of Cost Functions for Pilot's Arm Movement: The Case of Helicopter's Flying Aid Functions with Haptic Feedback

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Abstract. Force cueing and active control technology hold great opportunities in the next generation of helicopters. The overall goal would be to reduce the pilot workload and increase the situational awareness In this paper we present an approach to help in designing such forces through the understanding of human motor control and the relation that could be established with piloting an aircraft precisely pilot's arm movement. This method is based on the comprehension of the optimality criteria (cost functions and their weightings) within inverse optimal control combined with Fitt's experiment using an active side stick.

Keywords: Cost functions · Inverse optimal control · Pilot's arm movement · Fitt's law

1 Introduction

Helicopters, as a complex flying machine, have been the subject of great evolution since several decades; consequently, controlling such a machine has become a very costly task and requires a continuous attention. Arriving to the Fly by Wire commanding systems the workload of the pilot has been significantly increased and the idea of using haptic feedback started to be a very interesting solution to reduce such a workload and increase the situational awareness [1, 6].

As we know, in such a context, haptic feedback is using kinesthetic sense to find a new way to transmit some messages to the pilot that should be understood immediately. That's why forces that have to be implemented on side-sticks should be intuitive as much as possible.

The term intuitive here, has been the subject of many questions relative to the meaning of such a description of the force, and the manner it should be.

We propose in this paper an approach to have some answers to these questions through the understanding of human motor control and the relation that could be established with pilot's arm movement. This approach is based on optimal control theory

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combined with Fitt's task [2]. According to the optimal control theory natural movements are optimal after a learning phase. This optimality could be expressed by the optimization of a combination of cost functions that the central nervous system choose to coordinate many more degrees of freedom than necessary to accomplish a specific task [3].

According to Fitt's task, the performance of the movement is related to the task's difficulty and could be expressed through empirical values [2]. Within this approach, the performance of the movement could be expressed through the weightings of every cost function that should be in agreement with experimental data, and the way how it can vary with the difficulty of the task should give us new interpretations of the movement especially in the case of manipulating an active side stick.

Through these interpretations we should be able to design a force feedback that could help the pilot instinctively or may at least give a way to evaluate such forces.

The remainder of this paper is split into three sections, in the first one we introduce the notions used in this study like haptic feedbacks, optimal control and Fitt's task. The second one deals with the presentation of the basic ideas behind this research and the introduction of the method proposed. In the last section we discuss the results, concluding with its consequences on the future work.

2 State of the Art

2.1 Haptic Feedbacks

The control of a machine equipped with automated systems has been a very important field of research for many years especially when "human" have to keep his role in the loop as a commander so, he has to understand the communication present with such systems [4].

In our context, and as a powerful approach, haptic feedbacks were proposed, providing new channel of sensory transmission with the perception of contact forces implemented on control devises [5].

The interpretation of those forces require the use of muscles, tendons and articulations through multiple physiological receptors, combined with the role of the nervous system to understand the proprioceptive sensory information in the purpose of constructing a new representation of the body and muscle activity [4] and adapt a new strategy of motor control that respond and deal with the new information.

Several issues were highlighted when haptic feedbacks proved that it could be very useful on helicopters, as external aids able to maintain the pilot in the loop [7, 8, 21] especially when his mission has become a complex task that require a total coordination between him and the automated command systems. The main issue, is the ability of the pilot to interact with those feedbacks and for that many studies and approaches have suggested different ways to design such forces, like we can mention here as an example the direct haptic aid which consist of producing kinesthetic sensations that suggest the right direction to the pilot, also the indirect haptic aid which use the aspect of human in counteracting external forces implemented on the control device [8].

2.2 Optimal Control

Recent research on designing forces for active side-sticks, in the context of haptic feedbacks were based on the dynamics of visual errors [8], and to the best of our knowledge, there is not an understanding of the movement itself that is adopted to specify which force can suit and help the pilot in his manipulation.

Studies on human movement differs from discipline to another; there are theories that try to find principles behind human motion or just describe the observed one [3].

Being classified in the last category, optimal control theory confirm that human motor control is an optimal strategy in the coordination of different degrees of freedom of the body with respect of some criteria. In order to accomplish a motion, the musculoskeletal system offers a kinematic, dynamic and actuation redundancy with the use of many degrees of freedom than necessary. According to this theory, CNS selects the optimal criteria for the motor control through one or a combination of cost functions [3, 9–11].

Pointing tasks for human arm movement have been the subject of an intense research in this field and numerous plausible cost functions have been identified in the literature. Flash and Hogan proposed to minimize a kinematic criterion, the cartesian jerk [12] defined as the sum of the square of the third derivative of cartesian coordinates, for an arm movement in the horizontal plane only. The minimum torque change cost function which corresponds to the sum of arm joint torques first derivatives, was proposed by [13, 14]. The study used an arm model, studying plane movements. Many other criteria were identified like the geodesic model which suggests that the CNS select the shortest path in configuration space of Riemannian manifold with respect to the kinetic energy metric [15], energetic models which propose cost functions related to the minimization of work of torques [16] and neural models, designed to optimize the amount of motor neurons activity during multi-joints movement [17].

In order to find more optimal information about trajectories and with the progress of computational optimization and new algorithms coming from humanoid robotics field, combination of cost functions or hybrid cost function was introduced through the work of [18] where it was proposed to combine the hand force change and torque change criteria to determine the optimal trajectory of human arm movements in crank rotation tasks. Furthermore a combination of the absolute work of torques and the integrated squared joint acceleration was found as a hybrid cost function that fit the best the trajectory of an arm reaching a vertical bar [10].

The most important details in those hybrid cost functions is the weight associated to each criterion that seems to be like an indication of the participation's degree which the CNS is using while controlling the movement.

Based on recent research [3, 10, 11, 19, 20], an inverse optimal control technique is adopted to find such composite cost functions through the resolution of a bi-level optimization problem.

This technique is summarized within the following explanation:

The Global Cost Function

$$C(\alpha) = \sum_{i=1}^{n} \alpha_i C_i$$

With n is the number of criterion chosen Ci are the cost functions plausible for representing the optimality of the movement, and αi are the weighting associated to each cost function (Figs. 1 and 2).

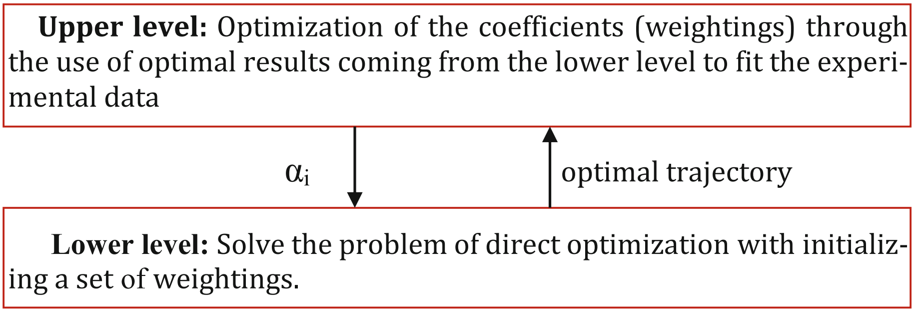

Fig. 1. Concept of the bi-level optimal control

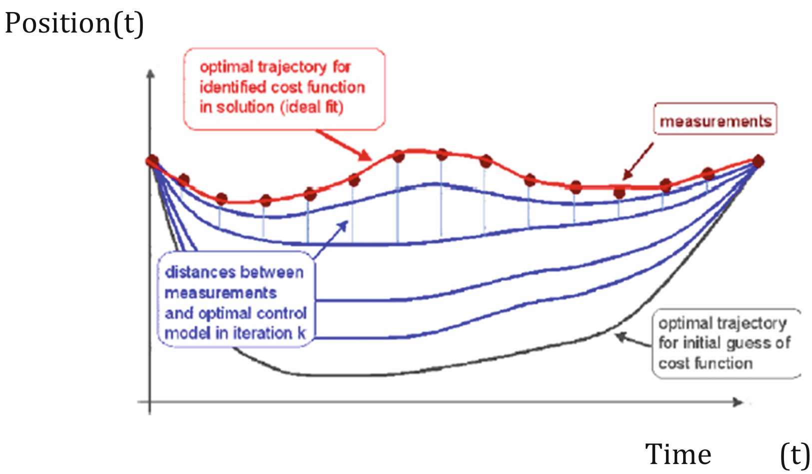

Fig. 2. Description of the goal of the bi-level optimal control: identification of cost function that fit the best experimental data [11]

Several methods were proposed to solve both levels depending on the arm model used and experimental conditions (task, limit of the movement…).

2.3 Fitt's Task

The control of the movement is a task that requires the integration of much information from environment and our neuro-musculoskeletal system, and the integration of such information determines the way how we control the movement. This process has been intensively studied from many experimental paradigms and discipline like biomechanics, cognitive science, and neuroscience.

Seen as both dynamical systems coupled, the actor and his environment interact with each other through forces provided by the user and sensory information structured by the environment [22]. Within the influence of physical constraint (forces) and sensorial one the subject adapts his motion, and many studies have been interested to explain this influence through tasks with speed accuracy trade-off [23].

In this context Fitt's (1954) [2] was the first who proved one of the most robust law governing motor control; an empirical law that measure the performance of the movement through a relation with the difficulty of the task (Fig. 3).

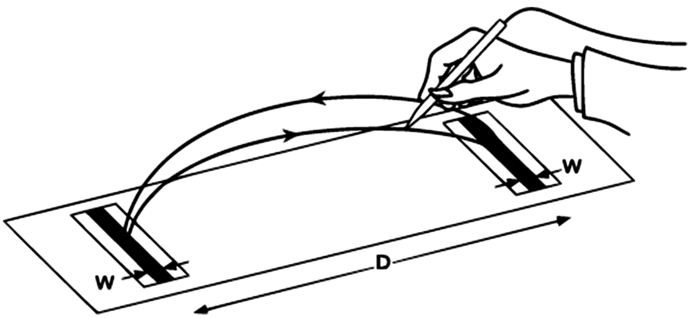

Fig. 3. Fitt's paradigm

According to Fitt's law, the time to perform an accurate pointing movement depends on the index of Difficulty (ID) defined as the logarithm of the ratio between target distance and tolerance (i.e. target size). This law predicts the movement time (MT) required to point a target of size W at a distance D:

$$MT = a + b * \log_2 (2D/W)$$

The term $\log_2$ (2D/W) represents the Index of Difficulty (ID) of the task and is expressed in "bits" measuring the quantity of information treated while accomplishing the task. The higher the value of ID, the more difficult the task is.

Realizing Fitt's paradigm consists in pointing targets as fast and as accurately as possible. It could be used as a methodological tool in order to evaluate the performance in the use of the input devices [22].

3 Contribution of the Article

The contribution of this paper is twofold: first we present the approach of bi-level optimal control as a tool to describe pilot arm movement manipulating an active side stick. An approach that could help to understand the underlying optimization criteria of pilot's motor control with a dynamical arm model and several cost functions which are plausible to describe the movement.

The second contribution is related to the integration of Fitt's law with the realization of a pointing task in a simulation environment. Within this simulation, the performance of the pilot and many other indexes describing the movement like the variability (it gives an idea about accuracy i.e. the space of the target reached by user) are measured while manipulating the same side stick.

Combining these two contributions, two different descriptive vision of the motor control in a pointing task using an active side stick are unified in one framework in order to find new ideas in evaluating and specifying haptic feedbacks.

To do so, in the present study, we propose a method based on experimental setup using an active side stick as a control device for Fitt's task in a simulation environment [22].

4 Method

4.1 Participants

Participants are 10 right-handed volunteers. Having no previous history of upper extremity musculoskeletal disorders and all reported normal or corrected to normal vision.

All participants were experienced computer users (we are not going to use pilot participants for the moment) but none of the subjects had prior experience with the interface used in this task.

4.2 Tasks

The participants had to manipulate a pointer in a computer screen using only the roll angular displacement of an active side stick (WITTENSTEIN). The position of the pointer will move horizontally following the position (measured in degrees) of the side-stick.

The participants are required to reach as quickly as possible two targets, having the same dimension, separated with a known distance, and situated in the horizontal plane.

The trial consist of trying to reach those targets as quickly and as accurate as possible with doing 50 cycle. One cycle is defined as attaining both targets one time starting from the middle position. The trial is considered successful if the rate of missed targets (overshoot or undershoot) is strictly inferior to 15 % and the participants have to perform the same trial again if the minimum performance level required was not attained.

4.3 Experimental Design

Each condition was characterized by a quantified Index of Difficulty (ID). ID = $\log_2(2D/W)$, the distance D (Fig. 4) is maintained constant and five widths W are used. The different values of the W parameter rendered a total of five experimental conditions with ID ranging from 3 to 7 bits with a 1 bit increment. The experimental phase was constituted by 8 trials for each of the different ID conditions. The order of the conditions was randomized to avoid any learning effect.

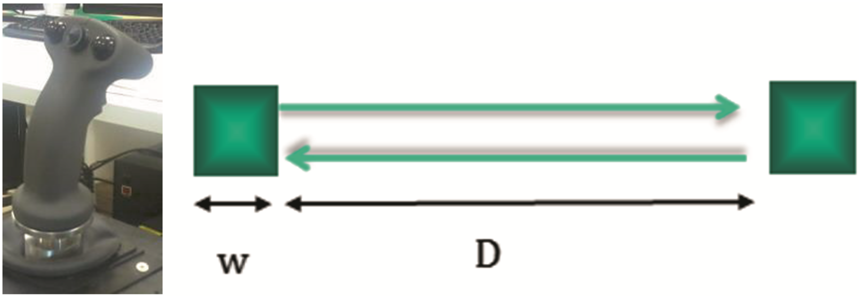

Fig. 4. Simulated Fitt's task & active side-stick

4.4 Experimental Setup

In order to applicate the bi-level optimal control, experimental data are needed and for that a specific setup was used to record the participant's motor activity from the 3D displacements of the upper limb segments and the electromyographic activities (EMG) in the effector space, with the position of the side-stick and the effort (forces) applied on it.

The 3D postures of the upper limb segments are recorded by four cameras optoelectronic (Flex 13 optitrack Motion System), at a 120 Hz frequency. Reflective markers are attached to specific places in the upper limb like the acromion for the shoulder and the lateral epicondyle for the forearm [24]. Following anatomical landmarks, joint angles could be reconstructed. EMG surface applied on group of Deltoid muscles pronator teres,

Fig. 5. System of motion capture

and brachioradialis muscles are recorded at 1980 Hz using a BIOPAC MP150 system with Ag/Ag-Cl bipolar surface electrodes (Skintact model FS 501, Innsbruck, Austria). Electrodes placement and locations were suggested by the SENIAM recommendations [25] (Fig. 5).

4.5 Data Collected

Through the experimental setup, data related to the kinematic of the upper limb segments EMG activity of the group muscles, the dynamic of the side stick (i.e.: it give an idea about the dynamic of end effector of the upper limb) are recorded by synchronizing the simulation of Fitt's task, the optitrack motion capture system and the BIOPAC MP150 system.

5 Human Arm Model

The use of an arm model is very crucial for the application of the bi-level optimal control problem as the purpose for the upper level is to find the best configuration of the arm (joint angles) that minimize a specific criteria. The use of such a musculoskeletal model even could enlighten us about some missing data that we could not reach by the experiment. That's why the work will be with XDE software which contains a big platform of several biomechanics models of the hole body seems to be a good solution to accelerate the research and avoid mistakes [26].

6 Discussion

For such a movement that was not yet explored, many cost functions were found from the literature that could be plausible to reproduce the optimal states of the motion. Based on pointing tasks essentially kinematic (jerk, acceleration, velocity, joint angles), dynamic (joint torques) energetic (work of torques) and neural models will be studied for our movement.

Finding all data needed for our arm motion using an active side stick in a Fitt's task (through the method proposed and the human arm model) and applicate the bi-level optimal control could lead us to a characterization of a task (could be simulated to piloting an aircraft in a slalom spot) within the variation of each cost function's coefficient.

The use of Fitt's task and the bi-level optimal control in this study lead to an evaluation of the performance of the motion through the variation of the weightings of each criterion (plausible to describe the movement) with the difficulty of the task.

7 Conclusion

In this study, we combine two different approaches to describe human motor control in order to give a better way to understand this complex task that the CNS seems doing daily.

Specifically, we are interested in pilot motor control in his arm movement manipulating the side-stick. The description of the method that we give in this paper could have an impact through the study of the influence of task's difficulties and haptic feedbacks on the performance of the movement and the variation of cost function's coefficient. That impact could help to design haptic forces in order to give a best way to assist the pilot's motion.

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