HUMAN IN THE LOOP CONTROL IN ROBOTICS FOR MANUFACTURING

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ABSTRACT

Traditional manufacturing processes are limited to either being fully automated (CNC machining, robotic packaging, robotic welding systems, etc.), or fully manual (assembly tasks, hand tool operation, etc.), with the automated processes being separated via safety barriers in work cells from the manual processes; however current collaborative robot systems are greying the divide in how human workers and machinery are separated in factories, by offering lower-risk force compliant systems which can reduce or eliminate the requirement for bulky and restrictive guarding. This progress toward guard-less machinery which can operate directly next to human workers opens up not only new ways in which technology can assist human workers; but also how human workers can assist robots.

Although collaborative robotics opens up new environments to operate in, many issues will remain which prevent the use of robots for new tasks, instead of human workers, due to a human's cognitive capabilities. Human-in-the-loop control systems may present a way for robots to expand their task capabilities by off-loading some of the cognitive processing to a human co-worker, forming a Human-Robot team which can perform greater than either used alone. This paper presents the results of early-stage testing of a human-in-the-loop system in which human participants controlled a simulated robot to accomplish a list of tasks. Manual and semi-autonomous control schemes were tested, where time to completion and number of collisions were recorded to measure the effectiveness of human-in-the-loop control over the fully manual system.

KEYWORDS: Control, Robot, Interaction

1. INTRODUCTION

1.1 Difficulties with existing industrial robotics

Robotics has had a large impact on industry since robots were first introduced to factories in the 60's, providing a level of precision, power and endurance which human workers cannot match. While robots have very clear advantages over a human worker with respect to these factors, several issues have limited their use in more widespread applications - capability, size and cost.

Regarding capability, or a robot's ability to accomplish a variety of tasks, perception of the environment is a key skill which robots are known to handle poorly. This particular skill has a host of implications regarding a robot's capabilities, such as affecting its ability to manipulate objects (e.g. if it cannot see an object in an unstructured environment, it cannot interact with it). This lack of skill in perception results in traditional robots requiring confinement to safety enclosures, with highly structured environments – in turn affecting the second issue of size, which limits the use cases for robots by the floor space it would occupy, compared to having human operators.

The floor space occupied by the robot is not only the actual dimensions of the robot, but includes the safety caging, along with any assistive object manipulation systems such as conveyors; however it is often the additional space-cost of safety caging which is a limiting factor in industrial robotic automation deployment.

Regarding cost, traditional robot systems will typically require specialist programmers and integrators to install a work cell, along with the required safety enclosures, resulting in large collateral costs being associated with a single automation task.

Collaborative robotics have helped to alleviate many of these issues a great deal, moving robots out from work cells, and onto work floors next to human workers. Passive and active compliant actuation has been the key driving technologies in reducing the risk of serious injury from robots, reducing the need for safety enclosures (saving space and cost), and opening up possibilities for programming by demonstration which allows minimally trained operators to rapidly program robots to perform basic automation where it is needed, saving cost and increasing capability by allowing for more rapid deployment without the use of expert programmers.

This new approach to robotics can be viewed as treating the robot as a *tool* rather than a *machine*, a tool which can be used if rapid automation for a specific task is required; however with robots now operating alongside humans, we can also consider how Human-Robot-Interaction (HRI) can be leveraged to improve the robot's capabilities through Human In The Loop (HITL) control.

1.2 Human in the Loop Control Systems

With HITL control, the objective is to integrate the human operator as a key part of the robot's control system. The exact manner in which the human is integrated can vary depending on what type of HITL system is being developed. As described in [1], HITL systems can be split into 2 overall categories, which each have 2 subcategories.

The first is having a human in the loop where they provide control input – this is then subdivided based on whether they are providing supervisory control, adjusting various parameters in a machine's control algorithm to get a desired response, or if they are providing direct control to the system.

The second is having a human in the loop where the human is being monitored – this is then subdivided into open and closed loop monitoring, where in open loop the human is observed and the information is then used in other parts of the robot's control system without feedback to the human, and closed loop is the case where some form of feedback is provided to the human.

A 3rd category exists which is for the case where we have a blend of a human providing control input while also being observed. An example of this would be in modern cars which have driver fatigue alert systems – here the driver is in direct control of the car, while the car is observing the driver to determine if they are alert. If the car determines the driver is not alert, is not responding to attempts to wake them, and is drifting out of the lane, then the car could attempt to make adjustments to maintain the car in its lane.

As well as benefits to the human operator of the system, HITL control could also allow robotic systems to take on challenges which have traditionally been too cognitively complex, either due to the actual task complexity or the complexity of the environment in which the robot must operate.

As described in [1], with HITL the human can serve several functions as part of the system, with the key ones being acting as a form of sensor for data acquisition, acting as a processing node for handling cognitive tasks, or acting as an actuator to interact with the environment. By using a human to fill-in capability gaps of the robot system in these ways, the capabilities of either alone are expected to be exceeded by their HITL collaboration.

We believe that advancement in HITL control will progress the new status quo of “robots as tools” to a situation where robots operate as true co-workers in general situations. By some accounts, it is believed that HITL can render a robot immune to an uncontrolled environment [5].

With regards the human-experience of incorporating robots to a shared workspace, there are many issues regarding safety-related trust; however with HITL systems there has been studies which have shown human operators have a greater sense of empowerment if they are part of the robot’s operation [2].

HITL control can however in some cases present a greater mental load on the human operator, specifically for tasks which are highly complex and dynamic, where human input may be requested for assistance in critical situations – a good example of this being in [3], where astronauts have reported in the past preferring to land their craft manually versus an HITL automated system as they found it difficult to mentally catch up with what was happening; whereas in manual control they were constantly “in the flow” of the changes as they happened.

1.3 Overview of Testing

The objective of the testing performed was to investigate the potential benefits of HITL control, and to provide early stage proof-of-concept data for a larger study which will be conducted in the coming weeks and months.

The test involved having human participants interact with a simulated robot, where they had to direct the robot through various navigation, search, and retrieval tasks in a home environment. The participant’s performance was quantified based on the time taken to complete each task, and the number of collisions between the robot and objects/walls in the environment.

Although this simulator testing was predominantly focused on the operation of a robot in personal assistance tasks, the focus of the research was the potential performance increase of HITL control – by having users complete tasks which a layperson would be familiar with, this testing can incorporate users from all demographics. We believe that this control paradigm can be extended to a manufacturing system, and intend to show this in future work.

2. METHOD

2.1 Test System Architecture

The control schemes implemented were a fully manual control scheme, and a semi-autonomous HITL system via a Microsoft Xbox controller and an Android app.

The HITL system incorporates the human for the purpose of cognition in the event a difficult task is encountered (e.g. finding a soft drink in a kitchen for the user), while relying on the robot's internal controller for more standard operations (e.g. navigating down a straight corridor).

While the robot is operating by its internal autonomous control, the user can provide a confidence rating which indicates how reliably the user trusts the robot will complete its current action – with reduced confidence the robot will operate at a reduced speed. If the user decides to take over direct control of the robot, the robot is given zero confidence and control is switched to the user.

Confidence is indicated in the app interface by the user placing their fingers on the tablet's touch sensitive surface in a specified control zone, with 1 finger being low confidence and 3 fingers being high confidence.

With the Xbox controller two schemes were explored where the user can either provide a discrete confidence signal which is all-or-nothing (press and release to turn on, repeat to turn off), or a continuous confidence signal which again is all-or-nothing (press and hold to turn on, release to turn off). These are referred to as "semi-autonomous 1" and "semi-autonomous 2" respectively in later discussion.

Two embodiments of the human control interface (see Figure 1) were explored for two reasons. Firstly since a significant proportion of those involved with the study were competent computer game users, it was predicted that they would possess an inherent advantage over participants that were unfamiliar and untrained with using conventional computer game controllers. Ensuring that at least one controller was unfamiliar to all participants provides a means of desensitising against such an issue. Secondly since the study sought to investigate how the robot's performance changes with increased levels of human interaction, it was felt that a purpose built controller would better facilitate higher levels of interaction than purely retrofitting a generic game controller built for multi-functional use.

(a) Xbox game controller

(b) custom built tablet control application

Figure 1: Human Control Interfaces. (a) Xbox game controller where left thumbstick was used for speed and direction control. The left trigger button was used for autonomy switching. (b) Custom built tablet control application. Coloured rings indicate speed, finger position in the circle dictated direction and the grey square at the bottom allowed the user to provide confidence ratings via finger placement.

A system overview for this controller is provided in Figure 2, which shows both the separation and integration of the Human (box labelled remote) and Robot (local) control. Autonomous control for the simulated testing is effectively a black-box controller, with automation provided through tools in the simulation software to guide the robot character to the goal points from the robot's current position.

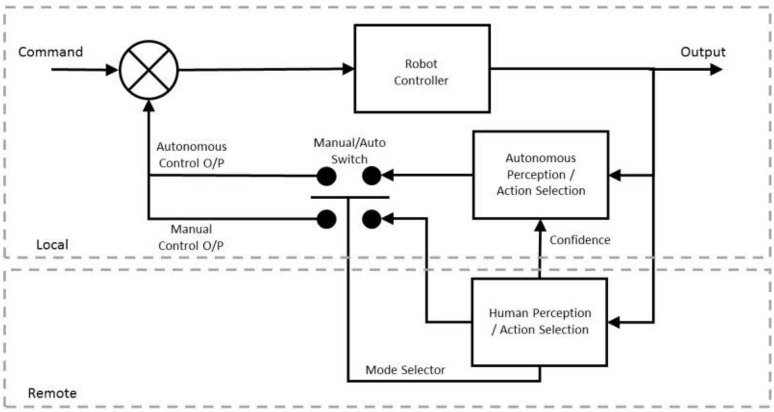

Figure 2: Human In The Loop Control Architecture, with dotted lines indicating what aspects are local to the robot and which are remote (i.e. part of the human process)

In our testing, the local component of this architecture ran on a desktop computer and was integrated to our simulation tool. The simulator used for this testing was Blender, a free open-source 3D modelling tool which provides a basic physics engine that was used to monitor collision situations. In the tests that were conducted, the local component of this architecture remained consistent.

We varied the form factor of the remote component of the test system, where one set of tests were run using a Microsoft Xbox controller and another set of tests were run using an application developed for an Android tablet, to investigate how a Human in the Loop control architecture depends on the form factor of the control interface. The Xbox controller communicated with the local system over a USB connection, and the application communicated via a wireless UDP link.

2.2 Testing Scenario

The test environment shown in Figure 4 was modelled to represent a standard home environment. Static and mobile obstacles were included in the environment to ensure the user was challenged, to prompt them into action. Static obstacles included furniture and doorways which had to be navigated around or through. Mobile obstacles included a robotic vacuum cleaner on patrol and a dog.

Key test metrics measured during testing were the number of collisions while completing particular stages and the time taken to complete particular stages. Testing was split into 3 stages, with the user beginning at the house's entrance. Stage 1 involved the user navigating to the kitchen to locate a drinks can from the start position. Stage 2 involved the user navigating to the bedroom and approaching a person to deliver the can. Stage 3 finally involved the user navigating the robot to a charging staging located in the home's hallway. Before users engaged with the full time trials, they were given a brief test-run to grow accustomed to the control interfaces.

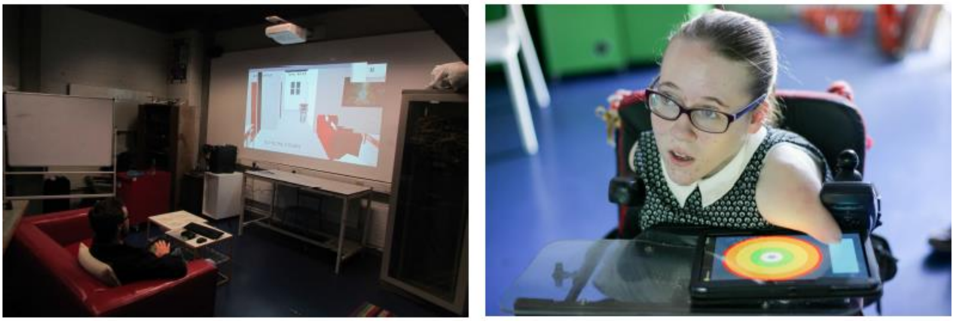

Figure 3: Testing setup for control schema, control application displayed.

It was found during preliminary testing that in an effort to record the fastest time users often placed little priority on avoiding collisions. To remedy this, a ten second penalty was added for every collision that the user incurred during the simulation.

A cumulative frequency distribution and bar chart conveying the overall time taken (with and without time penalties) for each controller across the sample set is presented in the results section.

Figure 4: Testing environment – Simulated home, which featured static and mobile obstacles such as furniture and a virtual dog respectively.

3. RESULTS

This initial study was undertaken with twenty volunteers. Of the sample set, 80% were students under the age of 25 and 90% of were male. The overall performance of the users was assessed based on two metrics; firstly their ability to complete the level in the fastest time and secondly their ability to avoid collisions in the process.

It can be seen in Figure 5 that when the performance of the users is notably improved in the use of semi-autonomous control, particularly when collisions become penalized.

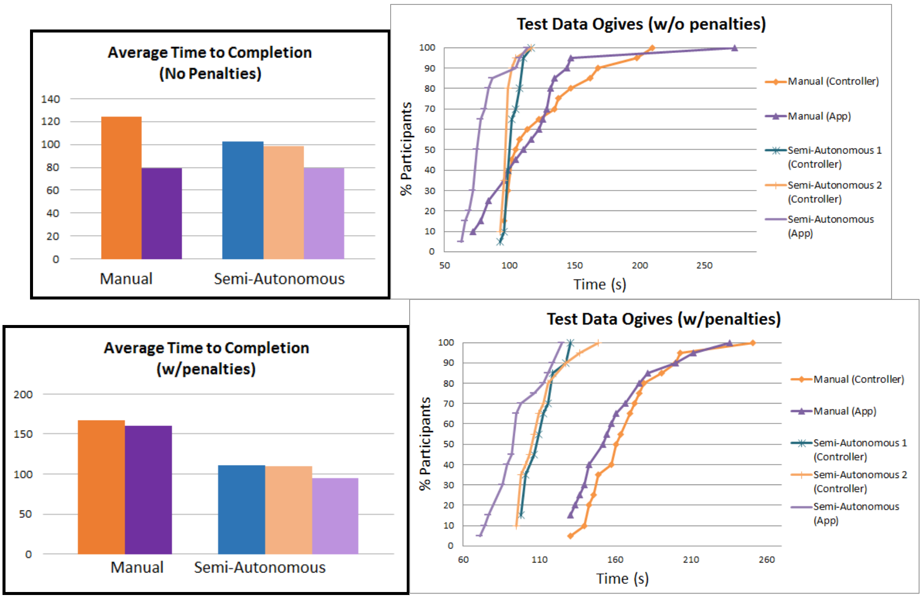

Figure 5: Results from testing, upper charts show test results where penalties for collisions are not included, charts below show results where a 10second penalty is applied in the event of a collision.

Lessons learned from the testing regarding the control interface design mainly concerned the usability of the control app. It was found that while users were generally quite effective in using it, they tended to have a higher number of collisions using the app compared to using the Xbox controller, as observed in Figure 6. This was attributed to general familiarity with the control of mobile objects with a games controller, versus unfamiliarity with the mechanics of the control app, as well as tuning issues in the control app where the robot's turning speed was deemed too fast. An additional point noted by the testers was that as the tablet lacked haptic feedback, users had to keep taking their eyes away from the robot to reorient their finger on the control surface.

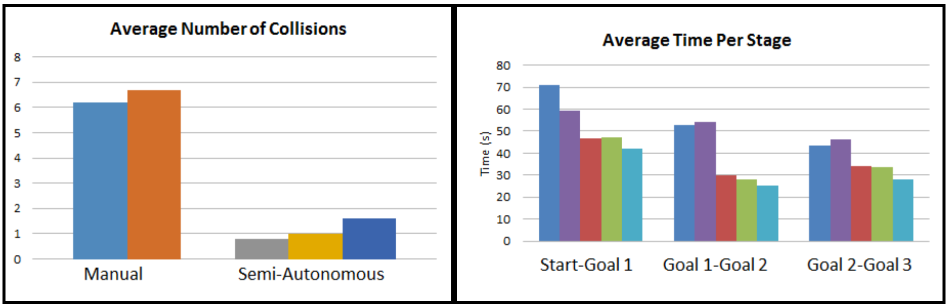

Figure 6: Average number of collisions, and average time per stage

It is also observed from these figures that the semi-autonomous control mode is better realised through a process of continuous switching than the less involved discrete-switching approach when implemented using the Xbox control embodiment. Once more this indicates that increased levels of operator interaction improve the performance of semiautonomous controllers.

It was found during testing that collisions were most likely to occur during movements which required fine-control and the spatial awareness of the operator with respect to the robot was low, e.g. manoeuvring the robot through a doorway while moving toward the operator.

4. FUTURE WORK

This stage 1 testing has provided key insights which will help direct an estimated further 2 stages of testing in the near-term.

Stage 2 will seek to implement improvements to the control app usability, in terms of tuning turning speeds etc., are minor changes which we predict will help further in demonstrating the benefits of HITL control. Furthermore, as this initial test set was limited in numbers and variation, future testing will be conducted in a more public high-footfall venue where we hope to be able to gather greater sample numbers and variation in user demographic to further support our initial findings. Similar quantitative data to stage 1 will be gathered, but also qualitative data through standard questionnaire methods.

In stage 3 it is projected that the issue of tuning parameters will be extended to develop a self-tuning system which can adapt the control scheme’s parameters to best suit the current user, based on qualitative data provided by the user and quantitative observations during trial runs. This adaptive system will be developed from the quantitative and qualitative data gathered in stage 2.

While these stages directly build on the platform presented here in a personal robotics context, it is expected that this research will feed into HITL research we are conducting in industrial mobile manipulation systems.

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