Probabilistic vs Linear Blending Approaches to Shared Control for Wheelchair Driving

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***Abstract*— Some people with severe mobility impairments are unable to operate powered wheelchairs reliably and effectively, using commercially available interfaces. This has sparked a body of research into "smart wheelchairs", which assist users to drive safely and create opportunities for them to use alternative interfaces. Various "shared control" techniques have been proposed to provide an appropriate level of assistance that is satisfactory and acceptable to the user. Most shared control techniques employ a traditional strategy called linear blending (LB), where the user's commands and wheelchair's autonomous commands are combined in some proportion. In this paper, however, we implement a more generalised form of shared control called probabilistic shared control (PSC). This probabilistic formulation improves the accuracy of modelling the interaction between the user and the wheelchair by taking into account uncertainty in the interaction. In this paper, we demonstrate the practical success of PSC over LB in terms of safety, particularly for novice users.**

I. Introduction

For people with mobility impairments, the ability to move around independently is important for their self-esteem and well-being [1]. The World Health Organisation estimates the number of people with mobility impairments to increase globally by around 250,000 to 500,000 people each year [2]. Many of these people, especially those with severe conditions, will need powered mobility, yet they are excluded from access to mobility because they cannot use commercially available interfaces for wheelchair control [3]. However, they could benefit from using a smart wheelchair that combines the user input with sensor data from the environment to execute motion reliably and safely [4].

A particular type of smart wheelchair that has emerged is the so-called shared controlled wheelchair where user's inputs are blended with information from sensors at each time step. Traditionally, shared control has been done as a linear blend of the user's intended velocity and velocity from a path planner. However, this linear blending has several flaws. For one, linear blending does not guarantee collision free movement in its theoretical formulation [5]. Secondly, in situations where there are multiple closely weighted estimates of any one of the user's velocity and the path planner's velocity, linear blending does not leverage this information to obtain a path planner's velocity that best agrees with the user's intentions. [6]

This paper implements a type of blending aimed at addressing the safety limitations of linear blending. In particular, we implement and evaluate a probabilistic blending of the user and path planner's intended velocity called probabilistic shared control (PSC), which explicitly models the blending of the user and path planner's trajectory in a mathematically principled way. Trautman hypothesised that PSC is safer than the traditional approach of linearly blending the human and path planner's trajectory [5]. In this paper, we show that PSC provides safer motion than LB and results in fewer collisions, especially for novice users.

The following section highlights other approaches to smart wheelchairs and how our proposal fits in this landscape. Section III briefly discusses the smart wheelchair's architecture, whilst Section IV discusses our proposed practical implementation of Trautman's PSC concept. Then Section V compares PSC to LB in a real world experiment and Section VI discusses the wider implications of PSC for smart wheelchairs.

II. Related Work

As already mentioned, several groups have proposed shared control strategies for wheelchairs that continuously blend the user input signal(s) with some sort of *optimal* control commands [7]–[11]. Generally these strategies use (variations of) the following equation to blend the user's input with the wheelchair's computed direction [5]:

$$\mathbf{u}^{LB}(t+1) = K_h\mathbf{u}^h(t) + K_R\mathbf{u}^R(t), \tag{II.1}$$

$$\text{where } K_h + K_R = 1, \tag{II.2}$$

and $\mathbf{u}^{LB}$ is the linear blended trajectory given to the wheelchair, $\mathbf{u}^h(t)$ is the human's intended trajectory at time, t and $\mathbf{u}^R(t+1)$ is the path planner's trajectory computed at time, t for the next time step, $t+1$. Most linear blending techniques differ in how the weight of the user's trajectory, K_h and the weight of the path planner's command, K_R are computed.

There have been attempts to use probabilistic models of the user's behaviour to improve shared control systems [12]–[14]. However, generally they do not model the actual *blending* of the human's intention and the path planner's command as a joint probability distribution. In contrast, we propose to improve the accuracy of the interaction model—between the user and the wheelchair—by explicitly taking into account uncertainty in the interaction and modelling

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Fig. 1: The smart wheelchair with two sonar sensor nodes at either side of its front. A further two sensor nodes are occluded at the rear of the chair.

this blending as a joint probability distribution. Therefore, in this paper, we implement a practical form of Trautman's theoretical formulation, where the user's intended trajectory and the path planner's trajectory are modelled as random variables [5].

III. System Architecture

In this section, we present our smart wheelchair architecture, which is built upon an Invacare Typhoon II powered wheelchair. At the heart of the electronics are two computing boards, the Radxa Rock Pro (for high level algorithms such as the shared control and localisation) and the Beagle-Bone Black (to interface with the sensors and the wheelchair control circuit). Both of these boards run the Robot Operating System on Linux. The system comprises several key modules namely: the sonar module, localisation module and shared control module. We will briefly discuss the first two modules before covering the shared control module in more detail the next section.

A. Sonar Module

We used popular, low-cost sonar sensors (HC-SR04) to detect obstacles in the environment. They were grouped into four nodes that each housed four sonars. Each node was easy to mount with minimal modification of the wheelchair and contained an Arduino micro-controller that directly serviced its own group of sensors. One node was fixed upon each of the wheelchair's castor wheels (Figure 1). To provide maximum coverage, the sensors were positioned so that they covered an area of about $150\,^{\circ}$. However, in this experiment, we only used three of the sonar sensors in a node to reduce sampling bandwidth and so the area coverage of each node was effectively $90\,^{\circ}$. The sonars were time-multiplexed to prevent cross-talk. The resultant sampling rate for the sensors was 5 Hz, which was sufficient for the wheelchair to move with the linear and angular velocities restricted to 0.2 m/s and 0.625 rad/s respectively.

B. Localisation Module

An internal representation of the obstacles in the environment is crucial for our wheelchair. Therefore, we constructed a local occupancy grid of the space around the wheelchair, which spanned an area of $4\,\mathrm{m} \times 4\,\mathrm{m}$ with a fixed grid resolution of $0.05\,\mathrm{m} \times 0.05\,\mathrm{m}$. The local map used log-odd update to populate the occupancy grids [15]. We updated the position of occupied grids using odometry, which was calibrated with our low-cost tracking toolkit, MoRe-T2 [16]. Occupied grids had a forgetting factor of 5 seconds, after which they become unoccupied [17]. The forgetting factor was used to suppress errors in estimating obstacle positions that might result from accumulated dead-reckoning error.

IV. Probabilistic Shared Control (PSC)

Here, we describe our practical implementation of probabilistic shared control (PSC) for the wheelchair application. We take Trautman's theoretical formulation as a basis [5]. However, we make several assumptions to realise PSC on a real-time wheelchair platform. These assumptions result in a usable implementation that maximises the joint probability distribution of two random variables: the user's intended trajectory; and the path planner's commands generated by the well-known dynamic window approach path planner (DWA) [18].

a) Assumption 1:

We assume both the wheelchair's and user's trajectories follow a probability distribution in the velocity space and the wheelchair uses DWA to generate its next velocity probabilities.

Using Assumption 1, we summarise our path planner based on DWA as follows. Firstly, let $\mathbf{u}_t^R = [v_t, \omega_t]^\top$ define the path planner's trajectory. Candidate velocities, $\mathbf{u}_{t+1}^{R_i}$ for the next time step are sampled from the dynamic window. That means these velocities are chosen according to the wheelchair's kinematic constraints such that they can be reached within the next time step and can be decelerated to zero before the wheelchair could collide with any detected obstacles.

Furthermore, each candidate velocity has a probability associated with it such that $\mathbf{u}_{t+1}^{R_i} \sim p(\mathbf{u}_{t+1}^{R_i} \mid \mathbf{z}_{1:t})$, $i = 1 : N$, where N is the total number of admissible and safe trajectories; $\mathbf{z}_{1:t}$ are the measurements taken of the robot's speed, and of obstacles detected in the environment up until time, t. A velocity's probability is computed based on its normalised clearance (the minimum distance to an obstacle along the trajectory [18]). We normalise this clearance by dividing the distance by the maximum distance at which our sonar sensors can detect an obstacle. For safety, we add a 10 cm safe zone around the wheelchair by ensuring trajectories with clearance less than this are given a zero cost and are therefore not selected.

b) Assumption 2:

The user's velocity distribution is based solely on the most current input command.

In general, the user's intended trajectory can be modelled as a random variable, $\mathbf{u}^h_{t+1} = [v_{t+1}, \omega_{t+1}]^\top$ with a probability distribution $p(\mathbf{u}^h_{t+1} \mid \mathbf{z}^h_{1:t})$ where $\mathbf{z}^h_{1:t}$ are the human's input measurements until time, t. However, we can simply assume the user's goal trajectory is approximately indicated by their current input command sampled at 10 Hz [8]. In other words, the probability distribution of the human's intended goal is assumed memoryless. The advantage of this probability distribution is that we simplify our framework, whilst simultaneously allowing users to change their minds and inherently allowing for a degree of input error. From Assumption 2, we have:

$$p(\mathbf{u}^h_{t+1} \mid \mathbf{z}^h_{1:t}) = p(\mathbf{u}^h_{t+1} \mid \mathbf{z}^h_t) = \delta(\mathbf{u}^h_{t+1} - \mathbf{z}^h_t). \qquad \text{(IV.1)}$$

c) Assumption 3:

A joint probability of the user's intended direction and the wheelchair's computed direction is simply the multiplication of the two independent variables and a coupling factor.

Trautman made the modelling assumption that:

$$p(\mathbf{u}^h_{t+1}, \mathbf{u}^R_{t+1}, \mathbf{u}^E_{t+1} \mid \bar{\mathbf{z}}_{1:t}) = \psi(\mathbf{u}^h_{t+1}, \mathbf{u}^R_{t+1}) p(\mathbf{u}^h_{t+1} \mid \mathbf{z}^h_{1:t}) p(\mathbf{u}^R_{t+1}, \mathbf{u}^E_{t+1} \mid \mathbf{z}_{1:t}),$$

where $\mathbf{u}^E$ represents the trajectory of obstacles in the environment. However, in this paper, we deal with solely stationary obstacles and so $\mathbf{u}^E$ has been ignored. $\bar{\mathbf{z}}_{1:t} = [\mathbf{z}^h_{1:t}, \mathbf{z}^R_{1:t}]^\top$. The "agreeability function", $\psi\left(\mathbf{u}^h_{t+1}, \mathbf{u}^R_{t+1}\right)$ [5], then takes the form below:

$$\psi\left(\mathbf{u}^h_{t+1}, \mathbf{u}^R_{t+1}\right) = \exp\left(-\frac{1}{2\gamma}(\mathbf{u}^h_{t+1} - \mathbf{u}^R_{t+1})(\mathbf{u}^h_{t+1} - \mathbf{u}^R_{t+1})^\top\right).$$

The free parameter γ controls how strongly $\mathbf{u}^h$ and $\mathbf{u}^R$ are attracted to each other and is currently set empirically. In our implementation, we normalise trajectories before computing the subtraction within the exponential function. This normalisation makes the exponential function more meaningful so that our agreeability function becomes:

$$\psi\left(\mathbf{u}^h_{t+1}, \mathbf{u}^R_{t+1}\right) = \exp\left(-\frac{1}{2\gamma}(\hat{\mathbf{u}}^h_{t+1} - \hat{\mathbf{u}}^R_{t+1})(\hat{\mathbf{u}}^h_{t+1} - \hat{\mathbf{u}}^R_{t+1})^\top\right)$$

where $\hat{\mathbf{u}}^h_{t+1}$ and $\hat{\mathbf{u}}^R_{t+1}$ are normalised velocities such that $\hat{\mathbf{u}}^h_{t+1}, \hat{\mathbf{u}}^R_{t+1} \rightarrow \left[\frac{v}{v_{max}}, \frac{\omega}{\omega_{max}}\right]^\top$. Using equation IV.1 and ignoring $\mathbf{u}^E$, our joint probability function is then:

$$\begin{aligned} p(\mathbf{u}^h_{t+1}, \mathbf{u}^R_{t+1} \mid \bar{\mathbf{z}}_{1:t}) &= \psi\left(\mathbf{u}^h_{t+1}, \mathbf{u}^R_{t+1}\right) \delta\left(\mathbf{u}^h_{t+1} - \mathbf{z}^h_t\right) p(\mathbf{u}^R_{t+1} \mid \mathbf{z}^R_{1:t}) \\ \Rightarrow p(\mathbf{u}^h_{t+1} = z^h_t, \mathbf{u}^R_{t+1} \mid \bar{\mathbf{z}}_{1:t}) &= \psi\left(\mathbf{z}^h_t, \mathbf{u}^R_{t+1}\right) p(\mathbf{u}^R_{t+1} \mid \mathbf{z}^R_{1:t}) \end{aligned}$$

d) Assumption 4:

The path planner's velocity that maximises the joint probability distribution is then selected as the control law of the wheelchair. This procedure is repeated for each time step.

The control law, u_{PSC} that describes our PSC implementation is given below:

$$\begin{aligned} \mathbf{u}_{PSC}(t+1) &= \mathbf{u}^{R*}_{t+1}, \text{ with} \\ \mathbf{u}^{R*}_{t+1} &= \arg\max_{\mathbf{u}^R_{t+1}} \psi(\mathbf{z}^h_t, \mathbf{u}^R_{t+1}) p(\mathbf{u}^R_{t+1} \mid \mathbf{z}^R_{1:t}). \end{aligned} \qquad \text{(IV.2)}$$

Our resultant implementation is expressed in Algorithm 1.

```
Let a be the maximum acceleration of the wheelchair;
Let d be the maximum deceleration of the wheelchair;
u_PSC = 0;
while True do
    Sample human input, z_t^h;
    Sample wheelchair's velocity, z_t^R;
    Sample obstacles, z_t^E;
    p_max = 0;
    if z_t^h == [0,0]^T then
        u_PSC = 0;
    else
        Compute set of admissible velocities,
         U^R = { u_{t+1}^{R_i} | u_{t+1}^{R_i} ∈ [u_t^R − dΔt, u_t^R + aΔt] };
        U^R ← remove unsafe velocities from U^R;
        foreach u_{t+1}^{R_i} in U^R do
            Compute clearance, c_i of u_{t+1}^{R_i};
            p(u_{t+1}^{R_i} | z_{1:t}^R) ← c_i / c_max;
            p(u_{t+1}^h = z_t^h, u_{t+1}^{R_i} | z̄_{1:t}) =
             ψ(z_t^h, u_{t+1}^{R_i}) p(u_{t+1}^{R_i} | z_{1:t}^R);
            if p(u_{t+1}^h = z_t^h, u_{t+1}^{R_i} | z̄_{1:t}) > p_max then
                p_max = p(u_{t+1}^h = z_t^h, u_{t+1}^{R_i} | z̄_{1:t});
                u_PSC(t+1) = u_{t+1}^{R_i};
            end
        end
    end
    Send u_PSC to motor controller;
end
```

Algorithm 1: Pseudocode for our probabilistic shared control (PSC) algorithm.

V. Experiment

To evaluate our probabilistic framework for the shared control of wheelchairs, we measured the performance and user acceptance when using PSC compared with using a standard linear blending (LB) approach. The LB control signal, $\mathbf{u}^{LB}_{t+1}$, was a simple linear combination (average) of the user's intended velocity and the planner's velocity indicating that we give equal importance to the user's input and DWA:

$$\begin{aligned} \mathbf{u}^R_{t+1} &= \arg\max_u p(\mathbf{u}^R_{t+1} \mid \mathbf{z}^R_{1:t}) \\ \mathbf{u}^h_{t+1} &= \arg\max_u p(\mathbf{u}^h_{t+1} \mid \mathbf{z}^h_{1:t}) \\ \mathbf{u}^{LB}_{t+1} &= K_h \mathbf{u}^h_{t+1} + K_R \mathbf{u}^R_{t+1} \\ K_h &= K_R = 0.5 \end{aligned}$$

A. Ethics Declaration

The experiment protocols were approved by the University College London Research Ethics Committee (ref. 6545/003) and experiments were performed in accordance with the ethical standards laid out in the 1964 Declaration of Helsinki.

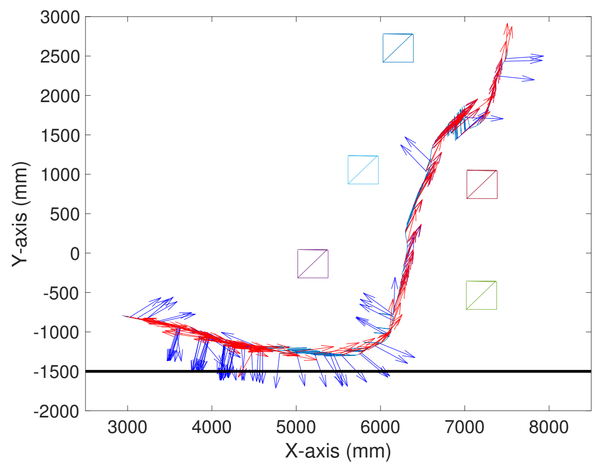


Fig. 2: Layout of the assessment course showing obstacles (rectangular cardboard boxes), the wheelchair's travel direction (red arrow) and the user's command direction (blue arrow) when driving with PSC. The thick black line represents a wall. Qualitatively, PSC is able to compensate for erroneous user input and generate a safe, smooth trajectory.

B. Participant Selection

We recruited 4 able-bodied participants (3 male, 1 female) and 3 regular wheelchair users (2 male, 1 female), aged 18-55 years. Two of the wheelchair users had tetraplegia from C4 spinal cord injuries; the third had right-sided triplegia. None of the participants had any problems impairments.

The able-bodied participants served as proxies for novice wheelchair users, as it was difficult recruiting large numbers of wheelchair users for all our experiments. This was justified since the wheelchair users we recruited had enough arm/hand strength to control a joystick, so they could perform any manoeuvre the able-bodied participants could do on a wheelchair, albeit perhaps with more grace. Thus, the main difference between both groups of participants was the level of experience.

C. Protocol

We performed two separate studies to compare PSC and LB. In Study 1, we asked able-bodied participants to manoeuvre forwards through some stationary obstacles (we used cardboard boxes to model obstacles so that any collisions would be harmless, as shown in Figure 2). We expected this task to be relatively easy to perform without shared control but as a reference point, we wanted to see how people used shared control when it was not really needed. We then went on to test some key navigation tasks from the Wheelchair Skills Test [19], namely: move forward; turn right around a corner; and avoid stationary people/obstacles whilst moving.

In Study 2, we wanted to see how participants used shared control for the much more difficult, but extremely relevant task of reversing into/out of an elevator. Participants started perpendicular to the small space so that they had to reverse-turn approximately 90° before entering the space/elevator.

For both studies, each participant performed four trials for each of the two types of assistance (PSC and LB) in a pseudo-randomised order, i.e. a total of 8 trials. Before switching to a new type of assistance, participants test-drove the wheelchair for up to 15 mins to become familiar with the task and the assistance. Participants were told which type of assistance they were using for all tasks, but were not given any indication as to one should be better than the other or not: they were simply described as different wheelchair *behaviours*.

D. Performance Metrics

We used several objective and subjective metrics to compare performance and acceptance between the two conditions (PSC vs LB).

For the objective evaluation, we used the standard metrics: distance travelled; task completion time; clearance and agreement [16]. Clearance is defined as the average minimum distance of the wheelchair from all obstacles for the duration of the task. For simplicity, the wheelchair was modelled as a rectangular footprint. Given an assessment course that stays constant, if an assistance mode is easy to drive with, we would expect our participants to cover less distance and take less time to complete trials than for a mode that is difficult to drive with. Similarly, for an assistance mode that increases safety, we would expect the clearance metric to be greater than for a mode that does not improve safety. We calculated these metrics from the wheelchair's global trajectory, recorded by our low-cost tracker, MoRe-T2 [16].

For the subjective evaluation, we asked participants to complete the IBM Computer Usability Satisfaction Questionnaire (CSUQ) to determine how participants perceived the different types of assistance [20]. We also invited participants to leave any free comments about the different types of control, and their experiences as a whole.

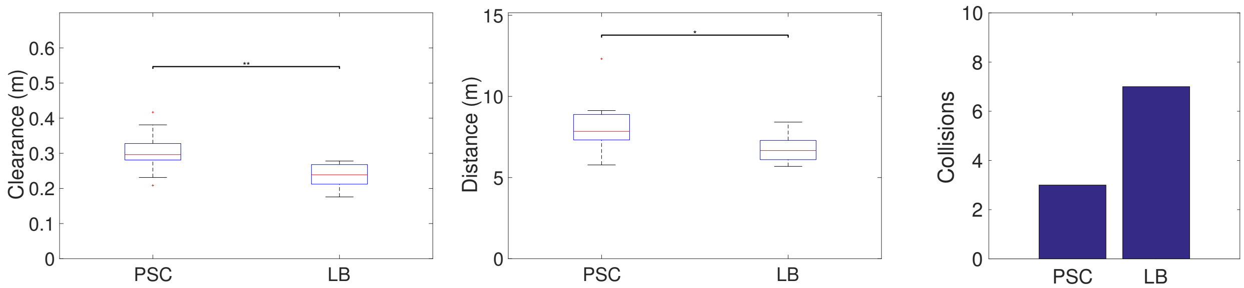
VI. Results

Interestingly, both studies and the different tests within them all produced very similar results, indicating that although the task and types of participants differ, overall, PSC performed comparably to LB. However, PSC provided safer motion (Figure 3(a)) with fewer collisions due to temporary sensor blindspots (Figure 3(c)), for both novice able-bodied participants and for regular users of wheelchairs.

A. Study 1 Results

PSC performed better than LB in terms of clearance (Figure 3(a)) , which supports the premise of PSC as proposed by Trautman, that it yields a safer method to blend the human's intended trajectory with path planner's trajectory [5]. However, the trajectories driven with PSC took longer and covered a greater distance than LB (Figure 3(b)).

1) Study 1 Objective Results: We compared objective metrics of the different types of assistance using the one-way ANOVA ($\alpha = 5\%$). Clearance was significantly higher for PSC (0.31 ± 0.05 m) than for LB (0.24 ± 0.03 m). Moreover, we only recorded a total of three collisions for PSC compared with seven for LB over all participants. Collisions with PSC were only light contacts with an obstacle (cardboard box) in a particular region about the wheelchair which were known

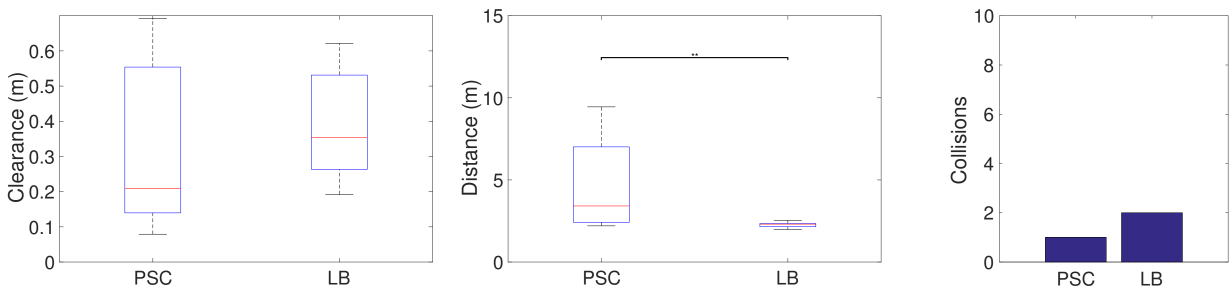


(a) More clearance is better, so PSC provided safer motion than LB ($** \implies p < 0.01$).

(b) PSC increased the distance travelled compared with LB ($* \implies p < 0.05$).

(c) A total of 7 collisions over all participants occurred with LB, compared with only 3 collisions for PSC. These were due to (temporary) sensor blindspots.

Fig. 3: **Able-bodied participants** driving forward, whilst avoiding stationary obstacles using Probabilistic Shared Control (PSC) and Linear Blending (LB).



(a) PSC and LB provided similar clearance for regular wheelchair users.

(b) Wheelchair users drove further with PSC compared with LB ($** \implies p < 0.01$).

(c) Over all participants, a single collision was recorded in total for regular wheelchair users driving with PSC whereas 2 collisions occurred with LB.

Fig. 4: **Wheelchair users** driving forward, whilst avoiding stationary obstacles using Probabilistic Shared Control (PSC) and Linear Blending (LB).

sensor blindspots. Four of the collisions with LB occurred in regions were the sensor were blind to obstacles and three occurs in regions where the sensor could detect the obstacle. Overall this result for collision indicates that on average, PSC made paths safer than LB. However, this safety came at a cost, since the distance travelled and task completion time using PSC (8.11±1.50 m in 144.81±165.40 s) were significantly greater than for LB (6.77±0.85 m in 79.60±85.69 s). On the other hand, an optimal path from the computer's point of view, might not actually reflect the trajectory that the user wants to follow.

2) Study 1 Subjective Results: We used a one-way ANOVA ($\alpha = 5\%$) to individually analyse each question of the CSUQ [20]. According to the results, PSC and LB both had similar levels of acceptance as there were no statistically significant differences in any of the tool's questions.

B. Study 2 Results

The findings for the task involving regular users of wheelchairs were slightly different from those of the able-bodied (novice) participants, possibly due to their better mental models and honed wheelchair skills. PSC provided comparable levels of safety (Figures 4(a) & 4(c)), again at a cost in terms of distance travelled and task completion time (Figure 4(b)). The significance of the Study 2 results was also tested using one-way ANOVAs.

1) Study 2 Objective Results: Clearance when using PSC and LB was not significantly different (0.32±0.22 m and 0.38±0.15 m respectively). However, we only recorded one collision with PSC compared with two collisions for LB. Similar to Study 1, collisions may be attributed to incorrect obstacle representation on the internal map of the occupancy due to (temporary) sensor blindspots. Again, similar to Study 1, the distance travelled and task completion time using PSC (4.60±2.77 m and 68.07±62.32 s) were significantly greater than for LB (2.26±0.16 m and 16.50±4.16 s).

2) Study 2 Subjective Results: We again used the one-way ANOVA to individually analyse each question of the questionnaire. For all but one of the questions from the IBM CSUQ, there was no statistically significant difference in preference for either PSC or LB. However, for the last question on the, "Overall, I am satisfied with this system", regular wheelchair users rated PSC (1.67±0.58) lower than LB (4.33±1.15) at a statistical significance of 5%. In the CSUQ, a rating of 10 means that the respondent strongly agrees, whereas a 0 means the respondent strongly disagrees with the statement. The qualitative feedback from the wheelchair users confirmed that they preferred assistance that did not completely stop their motion, even if the Shared Control indicated that no motion was the best of all the possible candidate velocities to ensure no collision. We may cautiously infer that perhaps, a more relaxed form of assistance that may allow collision but only at very slow speeds would therefore be preferred.

VII. Discussion

It is important to mention the limitations of our study. Our implementation of linear blending was a basic type of linear blending where we simply average the user's trajectory and path planner's trajectory. This averaging implied that we assigned equal importance or weighting both the user's input and autonomy. However, in most work in the literature, the weights are modulated based on some factors including safety, and agreement between user's and path planner's trajectory. Nevertheless, these weights still do not guarantee safety as proven by Trautman [5]. Thus, for the purpose of this initial implementation, it was sufficient to employ the simplest form of linear blending that is unbiased to either the user's input or the autonomy.

It should also be noted that we undertook two different studies with two separate groups of participants: able-bodied and regular wheelchair users. These different studies mean that we cannot directly compare the results from the two studies. However, we do see in both studies that PSC performs at least as well as (and sometimes better than) LB in terms of safety, albeit at a cost in terms of task completion time and distance travelled.

All participants commented that PSC was perhaps too cautious and would prevent them from moving into some spaces when they thought they had sufficient clearance. We are currently re-designing our smart wheelchair so that it is perceived as more agreeable to the intention of the user. In particular, we are modifying our agreeability function, γ so that the wheelchair optimises more for agreeability than it currently does and less for clearance than it currently does. Nevertheless, a cautious control may still be beneficial for people with very severe impairments. For such people, an improvement in safety may outweigh improvement in performance. Although there are other ways of improving safety in shared control systems, we have shown that PSC can explicitly embed the concept of safety.

VIII. Conclusion

Probabilistic shared control (PSC) offers an alternative, more generalised and powerful framework for combining the human's intended trajectory and the path planner's trajectory, compared with the de facto standard of linear blending (LB). It works by modelling the user's trajectory and the path planner's trajectory as a joint probability distribution, rather than linearly blending the two values. In this paper we have shown how we can make certain assumptions that allow a practical implementation for wheelchair driving to be derived from Trautman's original theoretical framework [5]. Moreover, we have performed some initial experiments, both with able-bodied participants and with regular users of wheelchairs, that demonstrate the feasibility of the approach. Our findings indicate that PSC does indeed provide safer motion with fewer collisions than the traditional LB approach.

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