RIDE: ROBOTIC INDIVIDUALIZED DRIVING EVALUATION

DESIGN AND PRELIMINARY EVALUATION

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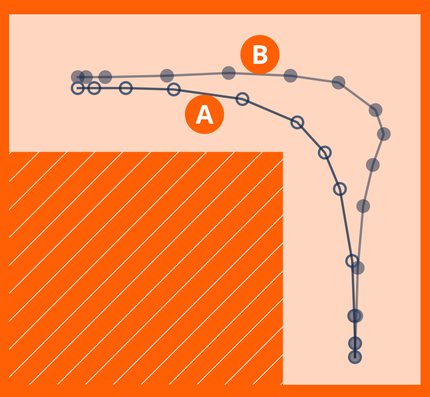


Figure 1. Left turn trajectories

I. INTRODUCTION

THE "BEST" DRIVING TRAJECTORY?

It depends on the power wheelchair user! Path A is more efficient, but B could be better for more severe or unique impairments (Figure 1).

Existing power mobility assessments do not formalize such context in objective and granular fashion, which the novel RIDE assessment aims to address (Table I).

TABLE I: POWER WHEELCHAIR DRIVING ASSESSMENTS

	Objective	Granular	Contextual
Clinical Ratings[1–4]			✓
Clinical Measurements[5–8]	✓	✓	
RIDE Model NEW	✓	✓	✓

[1] Kirby RL. Wheelchair Skills Test (WST). *Arch Phys Med Rehabil.* 2002;83(1)
[2] Mills T. Functional Evaluation in a Wheelchair (FEW). *Disabil Rehabil.* 2002;24(1–3)
[3] Mortenson WB. Wheelchair Outcome Measure (WhOM). *Disabil Rehabil Assist Technol.* 2007;2(5)
[4] Letts L. Power-mobility Community Driving Assessment (PCDA). *Assist Technol.* 2007;19(3)
[5] Cooper RA. Analysis of joysticks for power wheelchair driving. *IEEE Trans Biomed Eng.* 2000;47(7)
[6] Sorrento GU. Joystick control in power wheelchair driving. *J Neuroeng Rehabil.* 2011;8
[7] Dicianno B. Virtual power wheelchair driving performance. *Am J Phys Med Rehabil.* 2012;91(10)
[8] Hoenig H. Mobility device type: one size does not fit all. *Arch Phys Med Rehabil.* 2015;96(3)

II. METHODS

DESIGN

RIDE is based on a Markov decision process (Table II) using a robotic wheelchair (Figure 2). Utility U is computed via the Bellman equation,

$$U(s) = R(s) + \gamma \max_{a \in A} \sum_{s \in S} P(s'|s,a)U(s'), \qquad 0 < \gamma < 1$$

The transition function $P(s'|s,a)$ serves as the basis for *assessment profiles*, allowing clinicians to personalize the assessment to the client.

TABLE II: MARKOV COMPONENTS

		Driving	Implementation
State	$s \in S$	Position	Directed acyclic graph
Action	$a \in A(s)$	Heading	Rigid body dynamics
Reward	$R(s)$	Environment	Depth point cloud
Transition	$P(s'\|s,a)$	Uncertainty	Assessment profiles

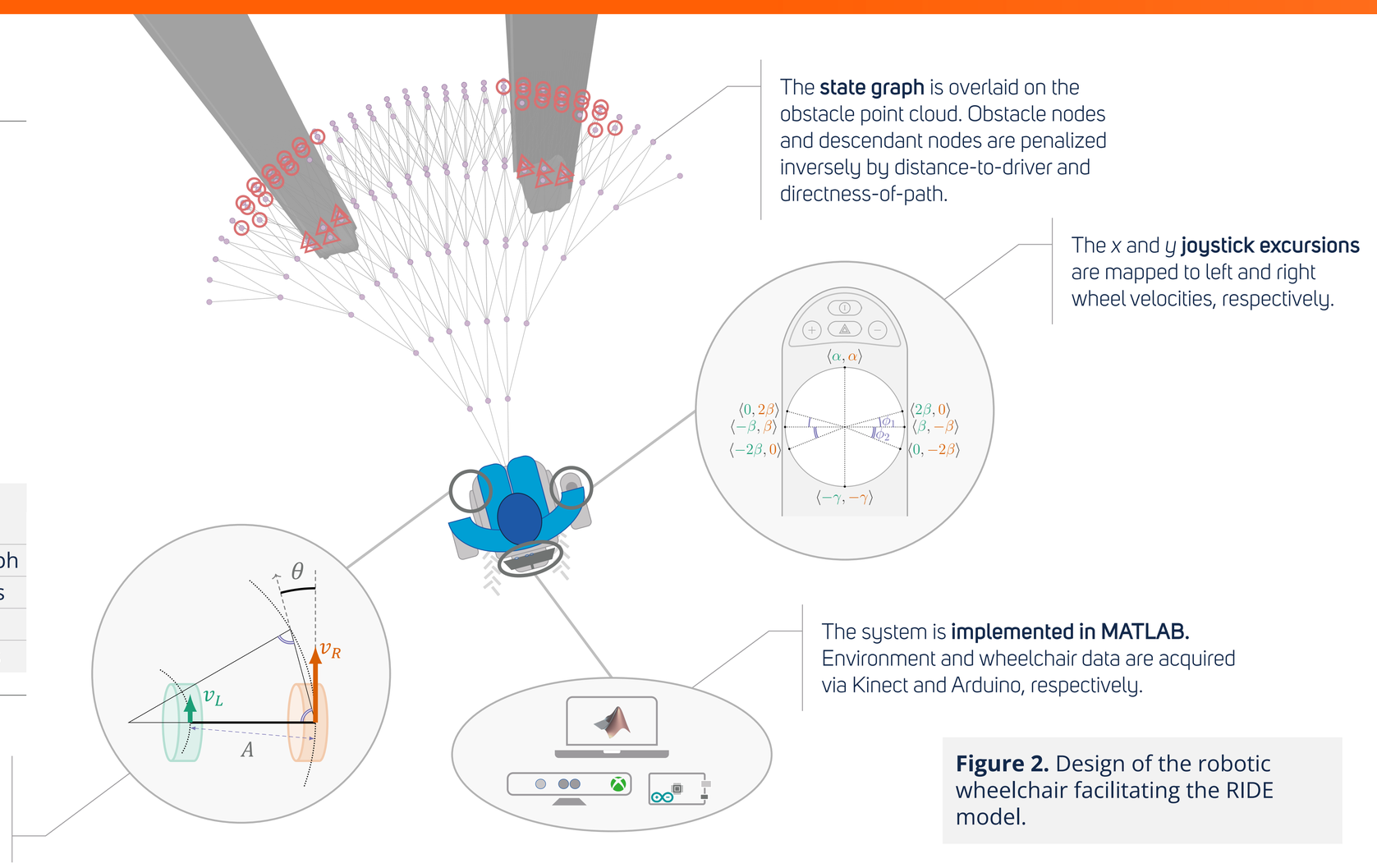


Figure 2. Design of the robotic wheelchair facilitating the RIDE model.

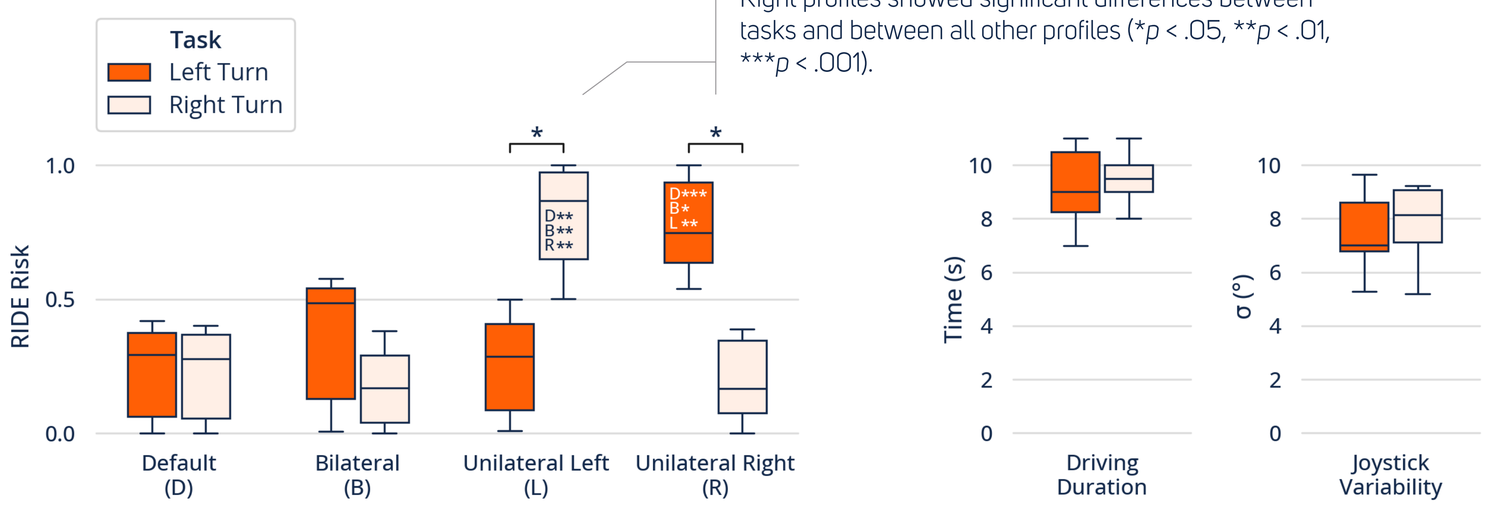


Figure 3. Inter-task and inter-profile comparisons of RIDE metrics and conventional metrics.

III. RESULTS

EVALUATION

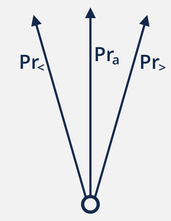
Using 4 profiles (Table III), RIDE risk Γ at time t was computed from optimal U and observed $\hat{U}$,

$$\Gamma_t = \sinh^{-1}\left(\frac{\hat{U}_t - U_t}{U_t}\right)$$

Aggregating across 2 tasks (left/right turn) and 3 subjects revealed significant differences in RIDE metrics but not conventional metrics (Figure 3).

TABLE III: ASSESSMENT PROFILES

	Pr_a	$Pr_<$	$Pr_>$
Default	0.98	0.01	0.01
Bilateral	0.90	0.05	0.05
Unilateral Left	0.90	0.09	0.01
Unilateral Right	0.90	0.01	0.09



IV. DISCUSSION

CLINICAL PROFILES

- Clinical decision-making relies on context
- Context can be difficult to formalize
- RIDE encodes contextual factors into a stochastic model

V. CONCLUSIONS

CLINICAL ASSESSMENT

- Conventional metrics are not sensitive to context
- RIDE metrics are sensitive to context
- RIDE profiles enable personalized rehab

VI. FUTURE DIRECTIONS

CLINICAL TRAINING

- Existing training is modest, transient[9]
- RIDE training could improve effectiveness (personalized), permanence (self-paced)

[9] Kirby RL. Wheelchair skills training program. *Arch Phys Med Rehabil.* 2015;96(11)