Drexel University College of Engineering

Smart Wheelchair: Brain-actuated and semi-autonomous assistive device interface

Mario De Lorenzo[1,2], Mohor Bhowmick[1], Kaustav Bora[3], Ashley Siddiqui[1], Hasan Ayaz[2]

[1]College of Engineering, Drexel University, USA
[2]School of Biomedical Engineering, Science and Health Systems, Drexel University, USA
[3]College of Computing & Informatics, Drexel University, USA

Contacts:
md3466@drexel.edu
+1 267-476-5225

Why the need for a Smart Wheelchair?

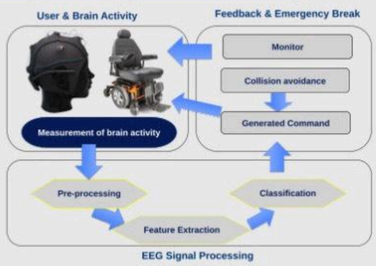
- **2.1 million people** worldwide are powered wheelchair users *(Simpson et al., 2008)*.
- **Up to 91%** would benefit from a smarter operating standard mobility device *(Simpson et al., 2008)*.

Conventional motorized wheelchairs' interfaces use:

- **joysticks**
- **head/chin control**
- **tongue control**
- **face/gaze control**

all of which require **fine motor control, continuous movement, or posture maintenance** that patients have difficulties keeping up *(Al Sibai & Manap, 2015)*.

Design and Approach



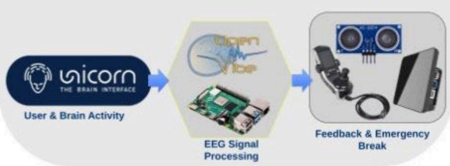


Fig. 1 Collision detection using Raspberry Pi and Ultrasonic sensor

Fig. 2 Connecting with the headset on OpenVibe

What is a Smart Wheelchair?

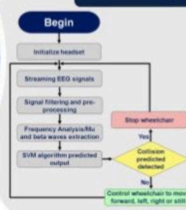
Our *Smart Wheelchair* will provide safe semi-autonomous driving without the need for muscle movements by implementing:

- **Motor-Imagery based mobile EEG-BCI** to control navigation
- **Collision avoidance sensors**

This assistive device interface will help people suffering from **locked-in syndrome** in order to **regain mobility and improve their quality of life**.

This *Smart Wheelchair* aims to provide greater accessibility and ease of use for severely disabled patients that can be installed in any motorized wheelchair.

Data Pipeline and Results



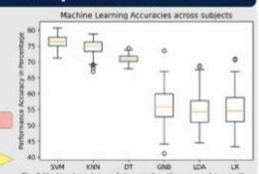
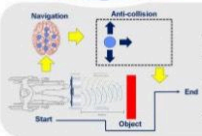


Fig. 3 Machine Learning prediction results with an open dataset with 109 patients. These are the results from 6 Machine Learning algorithms: Support Vector Machine (SVM), K-Near Neighborhood (KNN), Decision Tree (DT), Gaussian Naive Bayes (GNB), Linear Discriminant Analysis (LDA), and Linear Regression (LR).

Implementation



The experimental testing session consists of:

- **BCI-training,** the patient is seated on the Smart Wheelchair, an LCD monitor will show the MI tasks for execution to collect labeled data and train the model
- **BCI-test,** the patients execute the same MI to control the Smart Wheelchair to move around a simple circuit.
- **Safe navigation test,** examine the ability of the control system to safely navigate the patient to the desired location will be tested.

References

Al Sibai, M. H., & Manap, S. A. (2015). A Study on Smart Wheelchair Systems. INTERNATIONAL JOURNAL OF ENGINEERING TECHNOLOGY AND SCIENCES (IJETS), 4(1). https://doi.org/10.15282/ijets.4.2015.1.4.1033
Simpson, R. C., LoPresti, E. F., & Cooper, R. A. (2008). How many people would benefit from a smart wheelchair? Journal of Rehabilitation Research and Development, 45(1), 53–72. https://doi.org/10.1682/JRRD.. 6, pp. 1034–1043, Jun. 2004.

https://www.unicorn-bi.com/
http://openvibe.inria.fr/
https://www.vitalmobility.ca/Quantum-Q6-Edge-Power-Wheelchair.php
https://wallsheaven.com/photos/brain-mind/p/7
https://in.pinterest.com/pin/583145851742148958/
https://bit.ly/3MizY7G