Recurrent Neural Network-Based Intention Estimation Frameworks for Power-Assisted Manual Wheelchair Users: A Feasibility Study*

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I. INTRODUCTION

The growth of the aging population and the increasing need to support their autonomous and active participation in the community have significantly contributed to the advancement of mobility assistive technologies. One example of these mobility devices is a pushrim-activated power-assisted wheelchair (PAPAW). PAPAWs are hybrid mobility devices that can provide the benefits of both manual wheelchairs (MWCs) and power wheelchairs (PWCs) while reducing the negative consequences associated with the use of those devices [1]. PAPAWs work based on a collaborative control framework [2]. Therefore, it is essential to recognize the user intent through pushrim interactions to provide appropriate assist torque. In this paper, we investigate the feasibility of using a recurrent neutral network-based user intention estimation pipeline for PAPAWs.

In our previous work, we demonstrated the feasibility of using a clustering-classification pipeline to recognize manual wheelchair users' intentions during wheelchair propulsion [3]. Gaussian mixture models were used to label data as one of the following four states: "no-assist", "left-assist", "right-assist", "straight-assist". These states indicate whether PAPAW assistance is needed and in which direction should the assistance be. We observed high classification accuracy (>89%) when using commonly used machine learning models, such as random forest (RF), extra trees, and support vector machine. However, the proposed clustering-classification pipeline required human supervision for the labeling and feature analysis procedures.

In this work, we aimed to address the limitations of the previously proposed intention recognition framework in two steps. First, we implement a new clustering model to automate the labeling process and eliminate the need for human supervision. Next, we use recurrent neural networks (RNN) to predict wheelchair user intent from kinetic measurements (i.e., human input torque to the pushrims). Some of the advantages of using RNN models include eliminating the dependency on hand-crafted features and improving the generalizability of the classification models [4].

II. METHODS

Our dataset included kinetic measurements for a variety of common daily life wheelchair activities. More details about the experimental protocol are available in our previous paper [3]. Subsets of these kinetic measurements were investigated through a feature analysis procedure and used for the clustering-labeling task. Moreover, filtered kinetic measurements were used for classification. An overview of this clustering-classification framework is presented in Fig 1.

Clustering: In our previous work, we implemented a two-stage labeling procedure to achieve consistent and representative labels for user-pushrim interactions. In that model, we first identified 7 variations of user-pushrim interactions (i.e., forming 7 clusters) and relabeled those clusters based on their similarities/differences. However, this model required manual observation and manipulation of the clusters, which is not desirable in a clustering-classification pipeline. To address this limitation, we extracted and used relevant features to recognize the previously mentioned four user-pushrim interaction states (i.e., "no-assist", "left-assist", "right-assist", "straight-assist").

Classification: The torque measurements from both wheels were standardized and fed into the RNN as a two-channel signal array (Fig. 2). The recurrent layer consisted of 64 neurons and a recurrent unit of either a Gated Recurrent Unit (GRU) [5] or a Long-Short Term Memory Unit (LSTM) [6]. The recurrent layer is followed by a single hidden dense layer with a rectified linear unit (ReLU) as an activation function and a fully connected classification layer with a softmax activation function. We used the Adam optimizer with a categorical cross- entropy objective function [7].

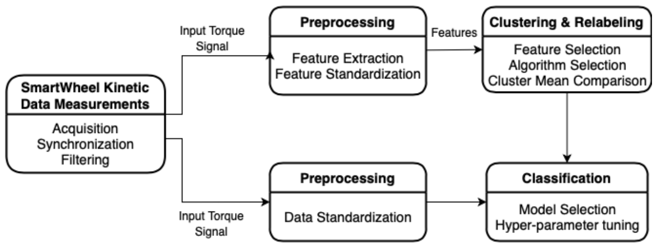

Figure 1. Overview of the clustering-classification pipeline

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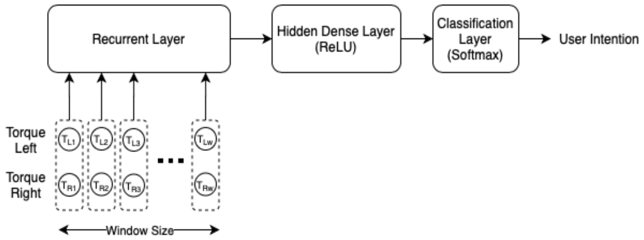

Figure 2. Classification network diagram

III. Results

Clustering: We found that the most representative labels were obtained when using torque inputs with a window size of 16 datapoints. We also realized that the mean value of the left and right wheels' input torque in each cluster was an appropriate feature to use to identify the desired 4 clusters of "no-assist", "left-assist", "right-assist", "straight-assist". As shown in Fig. 3, the proposed clustering model successfully identified the relevant clusters and consequently automated the relabeling process (i.e., from 7 to 4 clusters). The strength of this method is specifically in the identification of the "no-assist" state. As shown in Fig. 4, this state is mainly associated with the release and recovery phases of user-pushrim interactions.

Classification: The classification accuracy of the proposed RNN models and the previously proposed RF classifier is presented in Table I. When comparing the classification accuracy of the RNN models with RF classifiers, we observe only a minor increase in the classification accuracy when using RNN with a GRU layer (0.18% higher for participant 1 and 0.66% higher for participant 2).

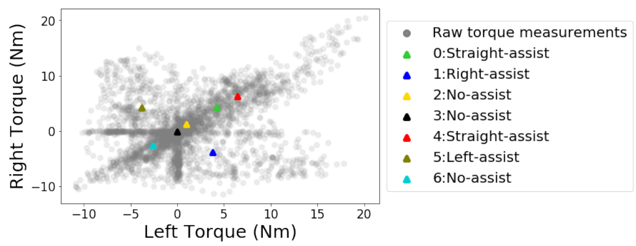

Figure 3. Visualization of the mean of the left and right wheels' torque for each cluster

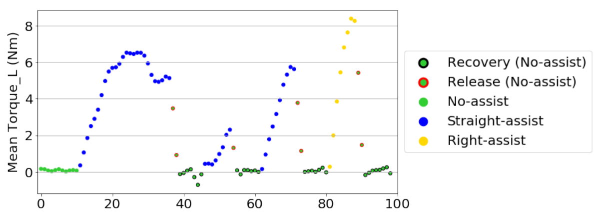

Figure 4. Labels assigned by the automated clustering model

TABLE I. Mean validation accuracy of RNN models and random forest classifier (3-fold cross-validation)

Classifier	Participant 1	Participant 2
GRU	90.90	91.09
LSTM	89.90	91.09
Random Forest (20 features)	90.72	90.43

IV. Discussion

In this paper, we sought to improve the limitations of our previously proposed intention estimation clustering-classification pipeline. We automated the labeling process by extracting relevant user-pushrim interactions that were indicative of user intentions (e.g., to perform a straight or circular motion). Moreover, we demonstrated the feasibility of using RNN to predict wheelchair user's intention from raw kinetic data. Both LSTM and GRU models were effective in recognizing the sequential dependencies of the torque measurement. When using RNN, the classification accuracy was slightly increased compared to the RF classifier. However, we hypothesize that the increase in the classification accuracy of RNN models increases with more complex datasets (i.e., a larger dataset with a variety of wheelchair activities). In our future study, we aim to train these models with a larger dataset and use transfer learning methodology to calibrate a network for each user.

V. Conclusion

Accurate identification of the user's intent is a significant step for designing a collaborative control scheme to provide appropriate navigational assistance during PAPAW propulsion. In this paper, we demonstrated the feasibility of using RNN models to predict user's intention while propelling the wheelchair. The RNN models eliminate the reliance on hand-crafted features by recognizing sequential dependency of the user input torque to the wheels. The findings of this study can contribute to the development of a more comprehensive and generalizable controller for PAPAWs.

References

[1] Giacobbi PR, Levy CE, Dietrich FD, Winkler SH, Tillman MD, Chow JW. Wheelchair Users' Perceptions of and Experiences with Power Assist Wheels. Am J Phys Med Rehabil. 2010;89(3):225–34.

[2] Cooper RA, Corfman TA, Fitzgerald SG, Boninger ML, Spaeth DM, Ammer W, et al. Performance assessment of a pushrim-activated power-assisted wheelchair control system. IEEE Trans Control Syst Technol. 2002;10(1):121–6.

[3] M. Khalili et al., "Development of a Learning-Based Intention Detection Framework for Power-Assisted Manual Wheelchair Users," in RO-MAN, 2020.

[4] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, "Deep learning for sensor-based activity recognition: A survey," *Pattern Recognit. Lett.*, vol. 119, 2019, doi: 10.1016/j.patrec.2018.02.010.

[5] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," *arXiv preprint arXiv:1412.3555*, 2014.

[6] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.*, 1997, doi: 10.1162/neco.1997.9.8.1735.

[7] D. P. Kingma and J. L. Ba, "Adam: A method for stochastic optimization," 2015.