Using Novel Walking Data to Personalize Intended Gait Speed Estimation for Lower-Limb Exoskeleton Users

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I. Introduction

The use of robotic exoskeletons in gait rehabilitation for people recovering from Spinal Cord Injuries (SCIs) can increase a patient's level of autonomy. However, fluency in the Human-Robot Interaction (HRI) is required to maintain the safety and efficacy of the treatment. HRI fluency is an abstract notion but can be roughly defined as the reliability with which the human and robot can predict each other's future actions [1]. It may be quantified by the inverse of the time taken to complete desired tasks. This time can be minimized if the robot can anticipate changes to the user's intent and assist as necessary. Intent itself is difficult to quantify, so the user's desired forward walking speed is considered as representing their intent herein. The goal of this work is to infer changes in an exoskeleton user's intended gait speed before they are fully realized.

Changes in walking speed correspond to changes in gait features such as step length, frequency, and joint angles. Thus, an exoskeleton user's intended gait speed may be inferred using this gait feature information. Previously, strategies such as Convolutional Neural Networks (CNNs) [2], Gaussian Processes (GPs) [3], gradient boosted decision trees [4], and Gaussian methods [6] have been used to infer user intent. These methods often require a large amount of training data, and acquiring enough data for users with SCIs is challenging due, in part, to increased gait variability. The research presented in this abstract (Fig. 1) describes a method to estimate intended gait speed while addressing data requirements and gait variability.

This work aims to address data scarcity by fusing trial data from uninjured users with data from novel users to personalize gait speed estimation. The main idea of the approach is that gait feature trends exhibit similarities across subjects, e.g., step length and frequency increase with speed. The estimator personalization developed in this work seeks to exploit these similarities and create a base dataset from uninjured subjects. As people with iSCIs are expected to show similar gait feature trends, this base dataset may then be transformed to provide additional training data for new users. Similar ideas for exploiting gait feature commonalities have previously been used to develop user-independent gait mode estimation approaches for healthy individuals [8].

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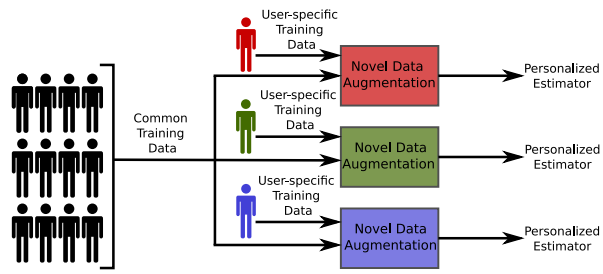

Fig. 1. Estimator personalization by using common and novel user data.

II. Methods

A. Novel Data Augmentation

1) Transforming Data From Uninjured Users: Data from healthy users walking in an exoskeleton may be easily obtained to satisfy the requirements of data-driven methods. These data still retain high-level similarities in gait feature trends (e.g., changes in step length with changes in gait speed [5]). This commonality between gait patterns may be exploited to increase the amount of available training data for injured users.

In this work, gait feature and gait speed measurements are approximated with Gaussian distributions; the data from healthy user trials are then transformed to match the mean and standard deviations of the data from an injured user. A transformation is performed on measurements of individual gait features $\mathbf{p}_s$ such that $s = 1 \dots S$. The vector containing measurements of a single gait feature is denoted by $\mathbf{p}$ and the subscript s has been omitted for readability. Its mean and standard deviation are $\bar{p}$ and σ respectively. Subscripts b and n are used to denote base and novel data respectively and n/b represents base data that has been transformed to match the distribution of novel data from a single user via:

$$\mathbf{p}_{n/b} = (\mathbf{p}_b - \bar{p}_b)\sigma_n \sigma_b^{-1} + \bar{p}_n \quad (1)$$

$$\mathbf{p} \leftarrow [\mathbf{p}_{n/b}^T \; \mathbf{p}_n^T]^T \quad (2)$$

The features, with N total measurements, are then collected in a matrix $\mathbf{P} \in \mathcal{R}^{N \times S}$ such that $\mathbf{P} = [\mathbf{p}_1 \dots \mathbf{p}_S]$.

It is important to choose appropriate novel data to ensure that the gait feature data carries a sufficiently high amount of information about the subject's desired gait speed.

2) Choosing Appropriate Novel Data: Steady-state walking in trials of subjects with iSCIs had a standard deviation of up to 0.18 m/s for their walking speed compared to 0.1 m/s seen in healthy users walking without robot assistance [9]. In addition to the severity of the iSCI, variability may

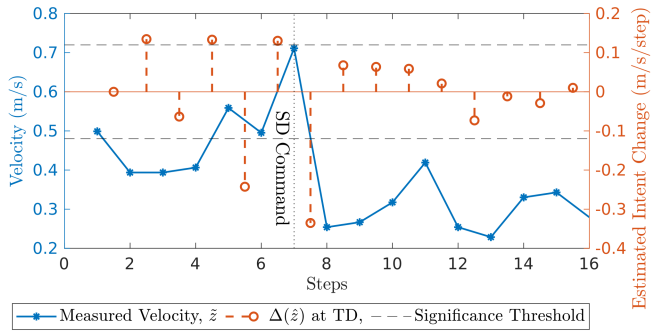

Fig. 2. Output of a single estimator trial for IU-2.

be affected by user fatigue, discomfort, or misfit orthoses. As a result, some walking trials may better represent the exoskeleton user's gait patterns than other trials performed on the same day. Therefore, choosing the appropriate training datasets from injured users is important to reduce noise in the data and accurately capture their gait patterns.

This choice may be increasingly difficult to make as the number of trials to consider increases. One way to achieve this goal while comparing probability distributions is to maximize the Mutual Information (MI) $I(V;P)$ between the distributions of the velocity V and gait features P. The distributions of these random variables may be estimated from collected measurements, with the MI of the two distributions then calculated as the Kullback-Leibler (KL) divergence between their joint distribution and the product of their marginals. Following this motivation, the base/novel data pairing with the highest MI was used in the estimator.

III. Results

Trial data was collected as part of a study approved by the IRB of the University of Notre Dame (Protocol 18-04-4650) [7]. One of the injured users, IU-1, had a complete SCI at the middle of the spine (T5) and the second user, IU-2, had an incomplete SCI from the middle to the lower spine (T8 to L2). All users were highly experienced in the use of the EksoGT. The subjects used the exoskeleton at a self-selected speed with the assistance of a walker and were at a steady-state gait before being issued a verbal command to either speed up or slow down. The trial sequence was pseudo-random and each subject underwent three SU and SD trials for a total of six trials.

A total of four steps spanning the speed change command were chosen as training data from all base and novel trials. Up to 12 steps' worth of data were selected as novel data for both injured users and used to transform the base data. The estimated change in desired speed was compared to the measured change and, if the speed change sign was correctly anticipated, it was considered a successful estimate.

Figure 2 visualizes the output of the estimator for an SU trial with IU-2. The stem plot represents the change in the estimated desired velocity of the exoskeleton user as estimated at TD; a positive value indicates SU and a negative value indicates SD anticipated for the subsequent MS. A

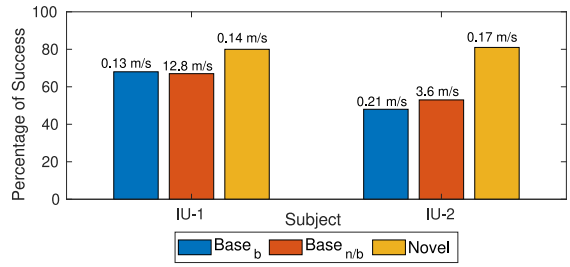

Fig. 3. Percentage of success with and without novel data for both subjects labeled with RMS error between predicted and measured gait speeds.

TABLE I
Confusion Matrix for IU-2
For Estimation with and without novel data

	Predicted SD			Predicted SU		
	Base $_b$	Base $_{n/b}$	Novel	Base $_b$	Base $_{n/b}$	Novel
Actual SD	50%	51%	78%	53%	45%	17%
Actual SU	50%	49%	22%	47%	55%	83%

significant speed change is expected after the vertical line as it represents the MS closest to when the speed-change command was issued. For an accurate estimate, the value of the signal in the stem plot should be positive for SU and negative for SD after the command is issued. Another metric considered while evaluating estimator performance was the root mean square (RMS) error between the predicted gait speed at TD and the value measured at the subsequent MS.

The estimator was run in three configurations for both subjects to highlight the benefits of using both novel and base data, as illustrated in Fig. 3. The confusion matrix for the trials of IU-2 is listed in Table I. The first configuration used untransformed base data (Base_b), the second used only the transformed base data ($\text{Base}_\text{n/b}$), and the third used both novel and transformed base data (Novel). The color of each cell ranges from green to red corresponding to accuracy – the higher the accuracy, the greener the cell.

Minor changes in SU/SD identification accuracy were observed when using only the transformed base data, as the accuracy depends on identifying only the speed changes, and not their magnitude. Despite increases in accuracy, the RMS errors deteriorated and were unacceptable at 12.8 m/s and 3.6 m/s for IU-1 and IU-2 respectively. Adding novel data to the transformed base data increased the overall speed change estimation accuracy from 48% to 80% for IU-2. These performance increases were achieved with only 12 steps' worth of data from the injured user. Overall, these results show that exploiting inter-subject commonalities in gait patterns can address data scarcity for injured users by enabling the use of data from healthy users.

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