Towards a Virtual Coach for manual wheelchair users

Brian French[1], Divya Tyamagundlu[1],Daniel P. Siewiorek[2], Asim Smailagic[2], Dan Ding[3]
[1]*Electrical and Computer Engineering Department, Carnegie Mellon University, Pittsburgh*
[2]*School of Computer Science, Carnegie Mellon University, Pittsburgh*
[3]*Human Engineering Research Laboratories, University of Pittsburgh, Pittsburgh*
{bfrench, divyatyam}@ece.cmu.edu, {dps, asim}@cs.cmu.edu, dand@herlpitt.org

Abstract

We introduce the concept of a Virtual Coach (VC) for providing advice to manual wheelchair users to help them avoid damaging forms of locomotion. The primary form of context for this system is the user's propulsion pattern. The contexts of self vs. external propulsion and the surface over which propulsion is occurring can be used to improve the accuracy of the system's propulsion pattern classifications. To obtain these forms of context, we explore the use of both wearable and wheelchair-mounted accelerometers. We show achievable accuracy rates of up to 80-90% for all desired contextual information using two common machine learning techniques: k-Nearest Neighbor (kNN) and Support Vector Machines (SVM).

1. Introduction

Persons with Spinal Cord Injury or Dysfunction (SCI/D) not only experience general functional declines that are associated with the aging process but also an increase in the prevalence of overuse-related musculo-skeletal injuries. There are well-documented reports of pain due to long-term reliance on the upper limbs for performing daily activities. Any loss of upper limb function impacts mobility and independence [1].

Upper limb pain is very common in manual wheelchair users, with carpal tunnel syndrome present in 49% to 73% of individuals [2, 3]. A recently published monograph provides concise ergonomic and equipment recommendations based on a review of published research [4]. The guidelines address reducing the frequency of repetitive upper limb tasks, minimizing forces required to complete tasks and minimizing extremes of wrist and shoulder motions.

There have been limited 'real-world' studies on persons with SCI who are non-ambulatory and use wheelchairs for their primary means of mobility. In order to understand the etiology of upper limb injuries and pain, it is necessary to monitor the actual usage of the upper limbs of persons with SCI.

2. Virtual coach

The goal of this project is to develop a Virtual Coach (VC) for manual wheelchair users. The design of Virtual Coaches for persons with disabilities is one of the main research thrusts of the Quality of Life Technology NSF ERC at CMU. Generally, a VC is a computer system capable of sensing relevant context, determining user intent and providing useful feedback with the aim of improving some aspect of the user's life.

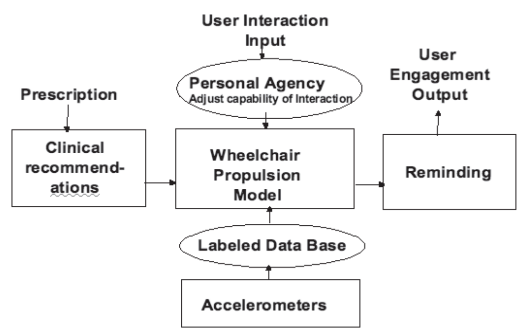

Figure 1: Virtual Coach architecture diagram

Figure 1 shows a top-level diagram of our VC system. It is composed of five basic modules. There are three forms of input supplied to the system; the prescription, the sensor data and user interaction. The sensor data can be compared against an existed, labeled data set. The user interaction input can be monitored by the personal agency module, in order to adapt to changing user capabilities. Each of these inputs are processed by the wheelchair propulsion model, which provides relevant feedback to the user.

The purpose of our VC is to recognize common wheelchair propulsion patterns in real-time and help wheelchair users, particularly novice users, learn patterns that are less damaging over the long term. Such a system would also provide researches with real-world data on patients' daily activity patterns and improve understanding of the correlations between different types of upper limb use with short-term and long-term injuries.

We introduced preliminary work on the propulsion pattern classification task using a wrist-mounted accelerometer [5]. We demonstrated achievable classification performance in the 70-90% range over a variety of surfaces. In the remainder of this paper, we describe the propulsion patterns in detail, outline the data collection protocol used in this study and provide more recent results at classifying propulsion patterns as well as other classification tasks relevant to the desired functionality of the VC.

3. Four wheelchair propulsion patterns

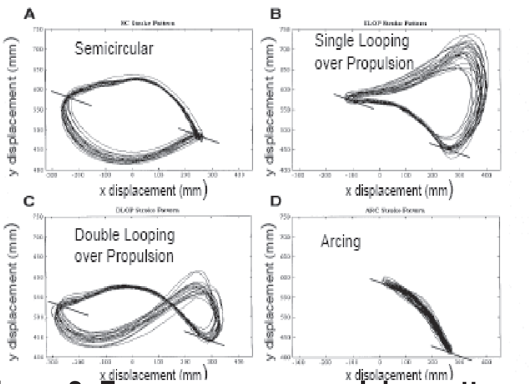

Figure 2: Four common propulsion patterns: (A) SC (B) SLOP (C) DLOP (D) ARC. The dark bars mark the start and end of the propulsive stroke

Figure 2 identifies the four common propulsion patterns: semicircular (SC), single loop over-propulsion (SLOP), double loop over-propulsion (DLOP) and arcing (ARC). A good wheelchair propulsion pattern should minimize stroke frequency and maximize the angle along the arc of the push rim from the start of propulsion to the end of propulsion [6]. The SC pattern has the properties of a good pattern, while ARC has properties of a bad pattern. Using a non-arcing propulsion pattern may lead to reduced risk of upper limb pain and injury [7].

4. Data collection methodology

The eWatch wearable computing platform [8, 9] was used to collect acceleration data from three subjects. The sample size was limited mainly due to time and availability of participants. One eWatch was worn on the subjects' dominant wrist. A second was mounted on the frame of the wheelchair with one accelerometer axis in the direction of motion and the other perpendicular to the ground. The accelerometers were sampled at a rate of 20 Hz with synchronized logs.

The subjects received training on how to properly perform the four propulsion patterns from colleagues at the University of Pittsburgh's Human Engineering Research Lab. For each pattern, data was collected on two surface types: a medium resistance surface (carpet) and a low resistance surface (tile). We previously found that surface resistance had the largest impact on classifier performance [5]. An approximate velocity of one meter per second was used, being within the range of average velocities of manual wheelchair users over tile and carpet [10].

Each subject collected four runs of each pattern over both surfaces. Each run consisted of constant velocity propulsion for 30 meters. For each subject/pattern/surface triple, we have 120 meters of propulsion data. We used an identical setup to collect data for subjects being pushed by another person.

5. Context relevant to VC functionality

The central classification task of the VC is to identify the user's current propulsion pattern. This directly affects the feedback given to the user, as the goal is to guide them towards using more efficient patterns. Related to this task is the ability to determine whether or not the wheelchair's motion is due to self-propulsion. Clearly, the system should not give feedback related to the user's propulsion pattern when they are being pushed.

The final classification task addressed in this paper is surface classification. This task does not directly reflect in feedback from the system, but is designed to improved performance of the propulsion pattern classifiers. We found that surface specific pattern classifiers have better performance than surface independent classifiers. By using a classification of surface type to multiplex several surface-specific pattern classifiers, we can improve the overall usefulness of the VC's advice.

All classification tasks were explored using two common machine learning algorithms, k-Nearest Neighbor (kNN) and Support Vector Machines (SVM) with a Radial Basis Function (RBF) kernel. These algorithms were chosen because they have been shown to perform well on classification of accelerometer data [8, 9]. We used MATLAB-Arsenal's kNN and SVMLight's SVM implementations. For all classification tasks, the data was segmented using 50%-overlapping windows. The window size and classifier parameters were determined using cross-validation on the training set.

5.1. Propulsion pattern

Optimal window size was found to be within the range of three to five seconds. For each window of data from the wrist mounted eWatch, a set of features, both time-domain and frequency-domain, were calculated. The features included: mean, standard deviation, root mean square, median absolute deviation, zero crossing rate, mean crossing rate, range, energy and entropy. Each feature was calculated over the X, Y and $X^2 + Y^2$ directions, leading to a total of 27 features per data point. We also explored the addition of root mean square and amplitude fluctuation features from the chair mounted eWatch to improve the classifier results.

5.2. Self-propulsion vs external pushing

Often when a wheelchair user is being pushed, their arms are at rest. In these situations the self vs. external propulsion task is trivial. However, it is possible for a user's arms to be in motion while they are being pushed.

To avoid the problem of having to differentiate between any non-propulsive arm motion and the four patterns, we explored differentiating between these two types of propulsion using data from the chair mounted accelerometer. The window size was set to 3 seconds. The features were computed by taking the absolute value of the FFT of each window in the X and Y axis directions. We addressed the binary classification task of differentiating between being pushed or using any of the four propulsion patterns.

5.3. Surface type

Building surface specific pattern classifiers leads to more accurate classification. Therefore, we need a reliable method of differentiating between different surface types. We explored using both the wrist mounted accelerometer and the chair mounted accelerometer data to discriminate between tile and carpet. The features computed from the wrist data were the same as described in Section 5.1. The features computed from the chair data were the same as described in Section 5.2.

6. Results

6.1. Propulsion pattern classification

Consistent with results reported previously [5], we were able to achieve single subject average classification accuracies in the range of 60-90% depending on surface type, see Figure 3. We suspect the reason for subject 2's outlier results are two fold. First, for that particular subject, propulsion was more consistent over the tile surface. Second, subject two was significantly taller than the other two subjects and the larger range of motion afforded by longer limbs may positively impact overall classifiability.

Since the literature indicates a stronger link between arcing propulsion and injury, we also explored a simpler binary classification scheme of arcing vs. non-arcing propulsion patterns. Table 1 summarizes the average classification results for arcing vs. non-arcing patterns over carpet and tile ± half of the range across subjects. The carpet classification accuracy is similarly higher than for tile. The average precision numbers for all tested classifiers are in the 89-93% range. The average recall numbers are in the 80-90% range. The variability of classifier recall is also slightly higher than that of classifier precision.

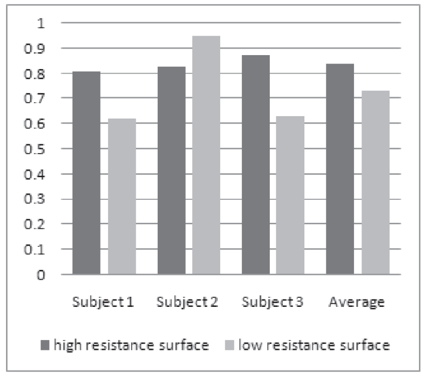

Figure 3: Average accuracy by subject/surface

Table 1. Average Precision(P) and recall(R) ± half the range between subjects, of arcing vs. non-arcing subject specific pattern classifiers

	SVM	kNN
Carpet	P: 0.9336±0.025 R: 0.8315±0.061	P: 0.9141±0.053 R: 0.8936±0.066
Tile	P: 0.9010±0.051 R: 0.8093±0.066	P: 0.8948±0.063 R: 0.8576±0.078

6.2. Self-propulsion classification

Table 2 summarizes precision and recall for the self vs. external propulsion classification experiments over carpet and tile. As can be seen, the results across subjects are relatively consistent with average accuracies in the mid-to-low 80's.

Table 2. Precision (P) and recall for the best self vs. external propulsion classifiers

	Subject 1	Subject 2	Subject 3	Average
Carpet	P: 0.9239 R: 0.9103	P: 0.9062 R: 0.8846	P: 0.7436 R: 0.7436	P: 0.8579 R: 0.8462
Tile	P: 0.8508 R: 0.8462	P: 0.8545 R: 0.8462	P: 0.8277 R: 0.7885	P: 0.8443 R: 0.8270

6.3. Surface classification

Table 3 summarizes the average precision and recall (± half the range) of the best performing single subject and cross subject surface classifiers using wrist, chair and combined data.

The wrist data contains modest discriminatory information for single subject classifiers with an average accuracy around 60%. Cross-subject classification is no better than random guessing on average.

The classifiers using only chair data were better performing in both the single subject and cross subject tasks. The chair data has discriminatory information for the acceleration profile of the chair without the noise of arm motion, as well as, vibration due to different surfaces. For single subject classification, the average accuracy is better than 90%, while for cross subject classification the average recall was around 70% and precision 80%.

Using features from both the chair and wrist datasets, the single subject classifiers average slightly lower performance than using only chair data, but have about half the variation. The average accuracy of the cross-subject classifiers is 5-10% better than chair data alone. This is interesting considering arm motion alone did not lend itself to discriminating across subjects.

Table 3. Average precision(P) and recall(R) ± half the range for the best surface classifiers.

	Single Subject	Cross Subject
Wrist Data (kNN results)	P: 0.6177±0.030 R: 0.5908±0.049	P: 0.5000±0.074 R: 0.4947±0.040
Chair Data (SVM results)	P: 0.9219±0.081 R: 0.9210±0.079	P: 0.8090±0.124 R 0.6981±0.206
Chair+Wrist (kNN results)	P: 0.8996±0.026 R: 0.8746±0.046	P: 0.8681±0.082 R: 0.7829±0.211

7. Conclusions and future work

In this paper we addressed several steps towards building a Virtual Coach for manual wheelchair users. We identified three forms of user context useful for the VC's task: propulsion pattern, self vs. external propulsion, and surface type. We showed that using common machine learning algorithms, average classification accuracies of up to 80-90% are achievable for all three forms of context.

Moving forward, there are several task yet to be address with respect to the VC. First, we need to explore differentiation between types of non-propulsion motion, such as turning, coasting, etc. Second, it currently seems that we may be able to simplify the surface classification into a small set of meta-surfaces based on resistance or surface texture instead of needing a separate classifier for all possible surfaces. Finally, we must combine the various context classifiers explored here into a complete system, where self vs external propulsion classification would be an enabling switch for the surface classifier, whose output would activate the most appropriate propulsion pattern classifier, whose output would inform the advice supplied by the VC to the end-user.

8. Acknowledgments

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