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Towards intelligent lower limb prostheses with activity recognition

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Abstract. User's volitional control of lower limb prostheses is still challenging task despite technological advancements. There is still a need for amputees to impose their will upon the prosthesis to drive in an accurate and interactive fashion. This study represents a brief review on control strategies using different sensor modalities for the purpose of phases/events detection and activity recognition. The preliminary work that is associated with middle-level control shows a simple and reliable method for event detection in real-time using a single inertial measurement unit. The outcome shows promising results.

Keywords: intent recognition – lower limb prostheses – pattern recognition – electromyography (EMG) – mechanical sensors – multi sensor fusion

1 Introduction

One of the most physically and mentally devastating events that can occur to a person is limb loss. There are more than 32 million amputees all around the world in which 75% accounts for lower limb amputees [1]. In England, the number of amputees and limb deficient people reach about 45,000 [2].

The use of prosthetic devices after amputation is one of the interventions to improve the amputees' quality of life. The commercially available prostheses related to lower limb extremity is divided into three types: mechanically passive, microprocessor-controlled passive and powered devices. The mechanically passive and microprocessor devices perform relatively well during simple activities (e.g. level ground walking). However, their inability to produce positive energy, when is needed in many activities (e.g. during stair ascent), is a serious limitation. Powered prostheses use active actuators to generate joint torque which result in powering the knee and ankle joints. Therefore, improved performance has been perceived in complex activities, such as stair ascent, compared to passive devices [3]. Pattern recognition (PR) is the most commonly used control strategy for powered prostheses. Young et al. used supervised PR algorithms to infer the user's intent in real-time [4]. High classification accuracies can be achieved by this approach, however; it requires an extensive collection of data for training the classifier [4]. The main challenge in the powered devices

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is the lack of direct control by amputees [5]. Therefore, the need to control the prostheses intuitively has brought the ideas of using surface electromyography (sEMG), mechanical sensors or a fusion-based control. One of the major sources of biological signals in neural control is electromyographic signal (EMG). Surface EMG (sEMG) electrodes have been used to record muscle activities signals from amputees wearing passive prostheses and powered prostheses [6]. Several studies investigated EMG PR to identify the user intent in different activities [5,7,8] for smooth, intuitive and natural control of prostheses. A number of studies have reported the use of mechanical sensors (inertial measurement units (IMUs)), load sensors and pressure-sensitive insoles) for lower limb activity recognition [6,9,10]. All these techniques have achieved reasonable recognition accuracies in steady-state, while the accuracy is much lower in transition between activities [6]. Sensor fusion-based PR for identifying different activities to improve the accuracy and responsiveness have been discussed in [6,11] .

Researchers have segmented the gait cycle in various ways to impose controlling strategy over the prosthesis. Many control algorithms have been implemented using machine learning techniques and simple rule-based approaches [3,12,13] to identify gait phases/events. However, none of the previous studies have dealt with transfemoral amputees (TFA). The aim of this study was to carry out a preliminary work for detecting events including initial contact (IC) and toe off (TO) in real-time using a single IMU. The idea of using multi-sensory system for further improvement in control of lower limb prostheses will remain to be investigated.

2 Control architecture for lower limb prostheses

The generalized control scheme for the lower limb prostheses consists of three level hierarchy as shown in Figure 1 adapted from [14]. The high level deals with the perception of user's intent based on the signals from prosthesis, environment and the user. The middle level controller translates the perceived user's intent to the desired output state (e.g. desired torque) after implementing detected phases and events. The low level control scheme deals with the feedback control of actuator dynamics for the desired movements (e.g. torque) related to the prosthesis.

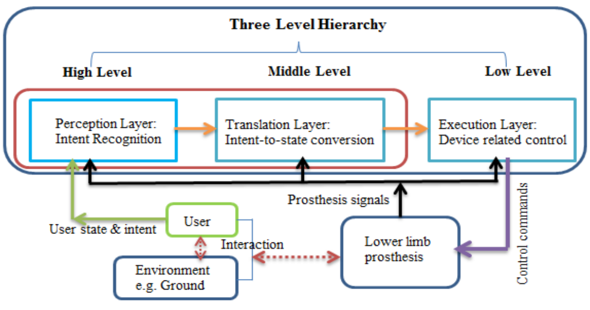

Fig. 1. Generalized control scheme for lower limb prosthesis

2.1 High level Control

In the high level control, several machine learning techniques were used for accurate identification of locomotive modes. These machine learning techniques require a series of steps including signal processing (filtration and segmentation), feature extraction (time domain, frequency domain and time-frequency domain), feature selection (filter, wrapper method) and classifiers based on unsupervised and supervised learning methods [10].

2.2 Middle level Control

Middle level control converts the estimated intent from a high level controller to a desired device state by dividing the gait into phases/events. A combination of temporal information, user or device states which are used to identify the gait phases/events, is the main difference between middle level and high level control [14]. The gait cycle (GC) is generally divided into two main phases: stance and swing phases. Some of the sub-phases include mid-stance (MSt), terminal stance (TSt), pre-swing (PSw) and terminal swing (TSw). Furthermore, GC can also be categorized in terms of events such as IC and TO. IC and TO mark the beginning of stance and swing phases, respectively. They are considered important events to objectively assess the gait progress. Accurate identification of gait phases or events is important for controlling lower limb prostheses. The C-leg for instance, is equipped with different sensors (strain gauges, angle sensor) for measuring bending moment, flexion angle and angular velocity of the knee joint. All these measurements detect the gait phases/events and provide necessary damping resistances for user's ambulation.

3 Preliminary work

3.1 Subjects and Experimental Protocol

One TFA (age: 52 years old; height: 166.1 cm; weight: 66.7 Kg) with two different types of prosthesis A: Ottobock 3R80 (knee) with College Park Venture (foot) and B: C-Leg (knee) with Ottobock 1E56 Axtion (foot) participated in this study. A & B refers to type of prosthesis in Table 1. The amputee had no other neurological or pathological problem apart from his amputation due to trauma leading to chronic infection of the knee. A written consent was obtained from the subject before proceeding for the experiment and the study was approved by the University of Leeds Ethics Committee. A 6-DOF inertial measurement unit (IMU) consisting of accelerometer and gyroscope (MPU 6050, GY-521) was placed at the interior side of the shank. A foot pressure insole with incorporated four piezoresistive based Flexi-Force sensors (Tekscan Inc., Boston, MA, US), was placed inside shoe for the detection of gait events and comparison with gyroscope data. The placement of IMU and foot switches can be seen in Figure 2. Once the subject was equipped with the suit, he was asked to perform level ground walking for about 10 m at different speeds (slow, normal, fast) and walk up and down along a 5.5 m on ramp with inclination of 5° at self-selected speed. 10 minutes break was provided in between these activities.

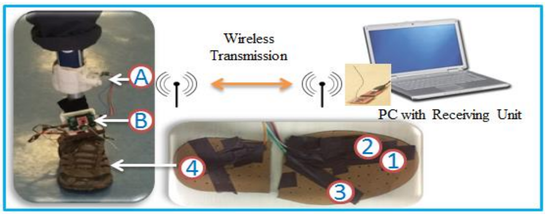

Fig. 2. Experimental Setup: Placement of Sensors; A: IMU, B: Base unit and Footswitches 1: Heel, 2: 1st Metatarsal, 3: 5th metatarsal, 4: Toe

3.2 Real-time Gait Event Detection Algorithm Description and Validation

Preliminary trials of two healthy subjects were conducted to develop event detection algorithm based on using signals from a gyroscope attached on the shank. The shank angular velocity signal shows distinct characteristic of positive peak (maxima) followed by two negative peaks (minima). Positive peak is known as Mid-Swing (MSw) and two negative peaks on either side of positive peak are known as TO and IC. The proposed algorithm is based on simple heuristic rules and evaluates each sample sequentially, hence facilitates in real-time implementation. The data was captured at a sampling rate of 100 Hz and then filtered out using 2nd order Butterworth low-pass filter at cut-off frequency of 10 Hz. In the start, the algorithm searches the maximum positive value and marks it as MSw after a threshold value greater than 100 degree/sec. Once MSw is marked, it searches for the immediate negative peak and marks it as IC. After IC detection, it waits for 300 ms, then searches the second minima and marks this as TO, provided that the angular velocity is smaller than -20 degree/sec. The threshold values were selected empirically based on the preliminary data. A sample of real-time event detection is shown in Figure 3.

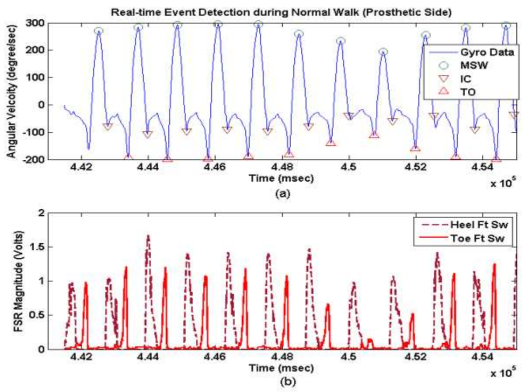

Fig. 3. Sample of real-time gait event detection using signals of (a) IMU (b) heel and toe off foot switches for validation Note: MSw: Mid-Swing, IC: Initial Contact, TO: Toe Off, Ft Sw: Foot Switch

3.3 Data Analysis and Results

The difference in timings from the gyroscope signal and two foot switches (heal and toe) was evaluated in terms of $difference = T_G - T_{FtSw}$, where T_G and T_{FtSw} indicate the timings of the detected events (IC or TO) from gyroscope and footswitches respectively. Table 1 shows the mean differences (MD) for different activities and comparing them with [15]. Positive and negative values indicate the delay and early detection respectively, when compared against footswitch approach. No other work has been carried out with TFA so direct comparison cannot be made with prosthetic side. However; this work is compared with healthy subjects reported in [15]. The MD and percentage increase/decrease (% I/D) of IC for prosthetic side was found to be slightly higher for level ground and ramp ascending whereas for TO it was significantly reduced for all activities when compared with [15] shown in Table 1 and Table 2. The significant improvements were obtained for intact side in terms of MD and % I/D.

Table 1. Mean Difference ± Standard Deviation, all expressed in milliseconds during detection of IC and TO between gyroscope and foot switches

		Level Ground Walk		Ramp Ascending		Ramp Descending	
Prosthetic Side	**Prosthesis**	**IC**	**TO**	**IC**	**TO**	**IC**	**TO**
	A	13 ± 34	13 ± 10	37 ± 28	23 ± 7.7	-13 ± 15	17 ± 11
	B	34.5 ± 30	-11.7 ± 13	18 ± 12	-34 ± 10	10 ± 25	-122 ± 44
	Total	**24.8 ± 33**	**-0.8 ± 17**	**28 ± 23**	**-5.5 ± 31**	**-1.2 ± 24**	**-53 ± 77**
Intact Side	A	11 ± 13	-44.6 ± 12	13 ± 13	-40.6 ± 6	11.5 ± 12	-41.5 ± 7
	B	2.5 ± 30	-32 ± 15	15 ± 7.7	-20 ± 11	5.6 ± 14	-32.5 ± 14
	Total	**6.4 ± 24**	**-38 ± 15**	**14 ± 11**	**-30.4 ± 13**	**8.5 ± 13**	**-37 ± 12**
[15]		**8 ± 9**	**-50 ± 14**	**21 ± 15**	**-43 ± 10**	**9 ± 20**	**-73 ± 12**

Table 2. % I/D of average mean error between this study and previous work [15]

		Level Ground Walk		Ramp Ascending		Ramp Descending	
% I/D		**IC**	**TO**	**IC**	**TO**	**IC**	**TO**
	Prosthetic	67.7 % (I)	98.4 % (D)	25 % (I)	87.2 % (D)	86.6 % (D)	27.4 (D)
	Intact	20 % (D)	24 % (D)	33.3 % (D)	29.3 % (D)	5 % (D)	49.3 % (D)

4 Conclusion and Future Works

In this study, a brief background was conducted on control of lower limb prostheses. The preliminary work showed overall low latency of the gait events detection for both prosthetic & intact side in real-time using single IMU at shank. Further work will include detection of phases/events with higher number of subjects and other locomotive modes. In addition, implementation of different classifiers to recognize various activities and user intent based on multi-sensor fusion for application of lower limb prostheses will be investigated.

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