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Smart Wearable Device for Real time Gait Event Detection during Running

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***Abstract*— Gait studies in sports and rehabilitation may benefit from online gait event detection algorithms for use in event-dependant feedback strategies. Event-dependant feedback systems may further benefit from durable, lightweight, low cost sensors for gait event detection. In this regard, this study describes the development and feasibility evaluation of an online gait event detection system using inertial sensor technology for the identification of Heel Strike (HS) and Toe Off (TO) events during treadmill running. Custom developed system software performs the online data acquisition, processing, graphical representations of lower extremity kinematics and online gait event detection. For increased robustness, a Finite State Controller architecture is employed for continuous detections of HS and TO during running. Pilot tests conducted with 7 healthy subjects during treadmill running verified the accuracy of gait event detection with mean timing errors of 14ms for HS and 27ms for TO compared to normative values. The effectiveness and robustness of gait event detection is promising signifying the use of the system for triggering event-dependant feedback during running gait retraining.**

***Keywords*— Inertial Sensors, Virtual Instrumentation, Gait event detection, Treadmill Running, Hardware/Software co-design.**

I. Introduction

Gait analysis is the systematic study of human locomotion, and gait event detection is an effective tool for measuring identifiable gait events to assist the analysis of gait [1]. Event dependant gait analysis has been extensively utilized for detection and treatment of pathological gait and for the development of gait assist devices with event centered feedback. Determining temporal events in gait studies is typically conducted using force platforms [2] although it restricts the analysis of gait to laboratory environments. A supplement to force platform data is the use of optical motion capture systems to obtain kinematic information of gait [3]. The detection of gait events using force plate and motion capture systems have been extensively researched with a variety of high accurate event detection algorithms [4-7].

However, these conventional systems lack the potential of being utilized in applications such as ambulatory gait monitoring and gait biofeedback, which initiated the use of wearable sensor technology for gait event detection studies. Accelerometers, gyroscopes and foot switches are to name a few, which were identified to be advantageous over conventional gait analysis systems due to their low cost, low power requirements and real time performance in unconstrained environments. Researchers involved in walking gait event detection studies have utilized wearable sensor technologies including accelerometers [7], gyroscopes [8] and foot switches [9] with promising outcomes in place of traditional gait analysis methods.

Although commonly seen in walking gait analysis, use of wearable sensors for gait event detection in running is seldom reported. The use of a single accelerometer for the detection of stance, step and stride durations during running is described in [10]; Davis [11] presented gait retraining with visual feedback for individuals with plantar fasciitis, patellofemoral pain syndrome and high tibial shock at ground contact using motion capture systems for gait event detection. However, these systems are high in cost and lacks the applicability for event dependant feedback applications. Such approaches involving running gait retraining with real time feedback can benefit from sensor based running gait event detection systems which can provide more flexibility in terms of cost, portability and real time performance.

In view of the limitations of gait event detection in running, this study describes the development of a novel real time system for lower extremity running gait analysis employing online gait event detection of stance phase using kinematical measurements. The system includes three triaxial inertial sensors for joint angle and angular rate measurements of the lower extremity joints and a custom developed software using LabVIEW software platform for online data acquisition and gait event detection. The reliability of gait event detection was tested on seven healthy subjects during treadmill running at a self selected pace. The gait event detection system described in this study is a part of a larger effort to be interfaced to a real time vibrotactile biofeedback[12] system for triggering phase dependant feedback during running gait retraining.

II. Method

A. Sensors

Microstrain's tri-axial Inertial Measurement Sensor Units (IMSU) were used in this study. The unit has a compact size of 41 mm x 63 mm x 24 mm and weighs 39 g. This study

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utilizes orientation and angular rate measurements. The unit has an orientation resolution less than 0.1°, accuracy of ±0.5° and supports data rates of up to 250 Hz over a sensor bandwidth of 1 – 100 Hz. The on-board processor handles compensation for sensor misalignments, gyro g-sensitivity and gyro scale factor non-linearity.

B. Software Development

The system software was developed using LabVIEW virtual instrumentation software platform. Software tools perform synchronous data acquisition, data validation, clinical representations of lower extremity joint measurements, gait event detection and data storing for post analysis. The software tools embedded are accessible to the user via an Interactive Graphical User Interface (IGUI).

During a training session, lower extremity joint motion is acquired and clinical representations of running gait are provided in the interface in real time. Concurrently, the gait event detection algorithm performs the detection of HS and TO events obtaining the joint angles and angular rates of lower extremity joint motions.

C. Hardware/Software Co-design

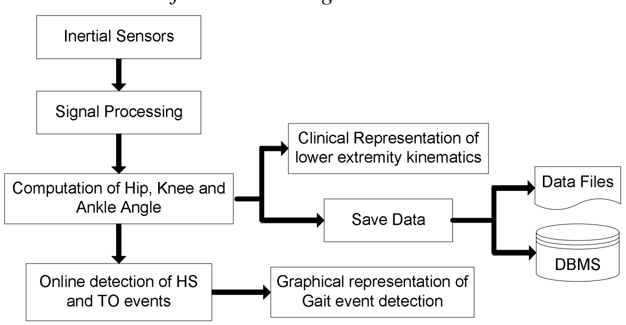


Fig. 1 Hardware/Software Co-design

The developed system incorporates three triaxial IMSU for acquiring lower extremity joint kinematics during running. Each IMSU placed on the thigh, shank and foot segments obtains the orientation and angular rate measurements of the hip, knee and ankle. The implemented software interface performs synchronous data acquisition from the sensors and graphically produces the lower extremity clinical representations of kinematic parameters in real time. Kinematic data are concurrently fed to the gait event detection algorithm which performs online detection of HS and TO events to obtain the stance phase of each gait cycle.

A Database Management System (DBMS) developed using Microsoft Structured Query Language (MS SQL) is linked to the user interface that supports saving subject and training session data for later referencing. Fig.1 illustrates the system architecture.

D. Online Running Gait Event Detection Algorithm

The gait event detection algorithm was developed using three kinematic parameters, namely hip angle, hip angular velocity and ankle angular velocity. The selected parameters were identified to be discernible at the instances of HS and TO events. Based on several gait cycles obtained during initial experimental records from two subjects during treadmill running, distinctive measurements for hip angle, hip angular velocity and ankle angular velocity were empirically chosen for HS and TO events from the readings. It was observed that at HS, hip is flexed producing a positive orientation angle ($\theta_{Hip}>0$), and at TO ($\theta_{Hip}<0$), hip is extended resulting in a negative hip angle. Discernible ranges for hip angular velocities were identified and empirical threshold values were determined at HS ($\omega_{HS1} \leq \omega_H \leq \omega_{HS2}$) and TO ($\omega_{TO1} \leq \omega_H \leq \omega_{TO2}$) based on initial data analysis. At HS, it was observed that ankle angular velocity undergoes a zero crossing point (ω_A = zero crossing) and that TO occur after its maximum negative peak during the gait cycle, for which an empirical threshold range was selected ($\omega_{TO1} \leq \omega_A \leq \omega_{TO2}$). Fig. 2 illustrates the discernible signal parameters occurring at HS and TO of running gait cycles.

In order to increase the robustness of event detection, a Finite State Controller (FSC) structure was incorporated to eliminate spurious detections of gait events. Finite state controllers are deterministic, with the next system state uniquely determined by the current system input in conjunction with the current system state [14]. The FSC consists of two states for HS and TO events. When HS is first detected, the FSC starts at state 1 and remains in this state until the inputs governing the detection of TO are reached. Once TO event is detected, the state transition occurs from state 1 to state 2, and FSC remains at state 2 until HS event is detected again. The sequential state transitions accommodated in the FSC removes false detections of gait events during running.

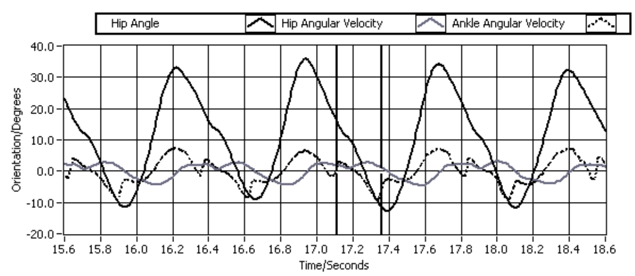


Fig. 2 Kinematic parameters identifying HS and TO events during Running Gait

E. Subjects

A total of 7 subjects, 3 females and 4 males participated in the test sessions. All subjects were young, healthy individuals with an average age of 24.7 years and Standard Deviation (SD) 0.76 years. All subjects completed written informed consent to participate in the experiment.

F. Experimental Procedure

The experiment included a one minute run on a motorized treadmill at a self selected pace. The three triaxial IMSU were placed on the lateral surface of the thigh, shank and foot for obtaining hip, knee and ankle joint motions respectively.

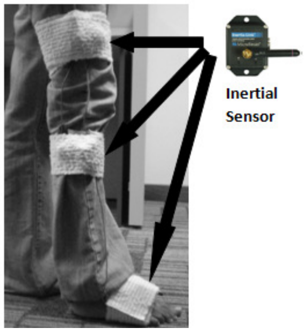


Fig. 3 Wearable Instrumentation for Running Gait Analysis

Each IMSU were securely mounted using elastic body straps and the initial angular measurements while the subjects were in upright position were recorded for calibration of readings. During the test sessions, the synchronous angle and angular rate measurements acquired from the sensors were graphically presented, and saved for data analysis. Fig. 3 depicts the wearable instrumentation for running gait analysis.

G. *Statistical Analysis*

To analyze the accuracy of gait event detection, the HS and TO event times were compared to normative HS and TO event time occurring during running. For each gait cycle, normative HS time was at 0% of a gait cycle and TO time was at 40% of a gait cycle [14]. For accuracy computation, 20 cycles from each subject was extracted, and the timing errors of early detections, late detections, Root Mean Square (RMS) of the True Error (TE) and their percentile gait cycle errors were computed against the normative gait event times. Using the technique described by Bland and Altman [15], the timing variations between the detected event times and the normative times were further elaborated.

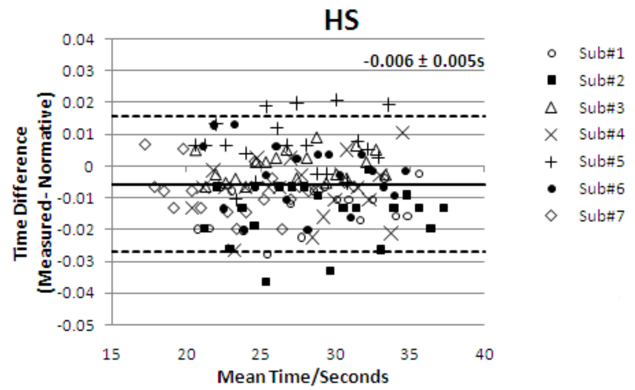
III. RESULTS

Agreement between the developed gait event detection algorithm and the normative event times are shown in Table 1. For HS, the mean RMS timing error for early detection and late detection was 13.0ms and 5.0ms respectively, and the gait cycle error was 1.4% and 0.6%. TO exhibited larger timing errors with 6.0ms and 28.0ms for early and late detections respectively and gait cycle errors of 0.8% and 3.3%. RMS True errors for both gait events remained less than 30ms, and gait cycle errors less than 4%.

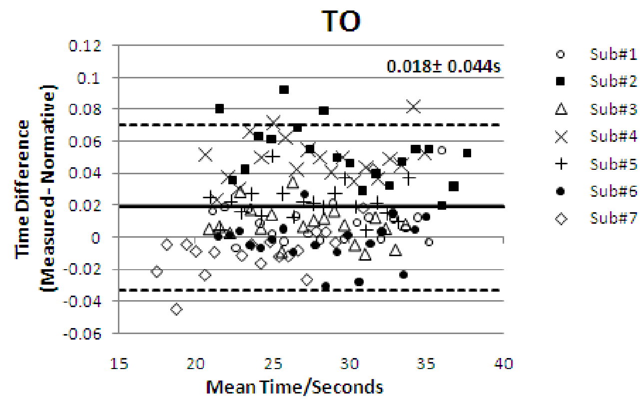
Fig. 4 illustrates the Bland-Altman plots for the two gait events HS and TO with mean time for each event detection plotted against the time difference between measured and normative event times. As illustrated on the plots, TO event demonstrated larger variations in the mean as compared to HS. Bland-Altman plots clearly illustrate the between-measurement differences allowing direct insight into the variability of event detections in terms of inter-subject and intra-subject variability.

TABLE I
RMS TIMING ERRORS (IN MILLISECONDS) AND GAIT CYCLE ERRORS FOR HS AND TO BETWEEN DETECTED EVENT TIMES AND NORMATIVE VALUES

Event	HS	TO
RMS Early Detection Error (SD)	13.0 (10.0)	6.0 (8.0)
RMS Late Detection Error (SD)	5.0 (4.0)	28.0 (17.0)
RMS True Error (TE) (SD)	14.0 (9.0)	27.0 (18.0)
Early Detection % GC (SD	1.4 (0.6)	0.8 (0.9)
Late Detection % GC (SD)	0.6 (0.5)	3.3 (2.1)
True Error % GC (SD	1.85 (1.1)	3.7 (2.1)



(a)



(b)

Fig.4 (a) Bland-Altman plot for HS (b) Bland-Altman plot for TO. The solid horizontal line denotes the mean of all timing errors for all subjects and the dotted lines denote the ± 2 SD.

IV. DISCUSSION AND CONCLUSION

The objective of this study was to develop an efficient online gait event detection system and test its detection accuracy for use with a real time vibrotactile biofeedback system. With regard to the timing accuracy of each detected event as compared to normative time values, the average of the RMS Early detection and late detection errors over all subjects for HS was 13 ms and 5 ms respectively, indicating larger timing errors due to detection of HS prior to the true occurrence of HS. Conversely, for the TO event, larger RMS timing errors were reported for late detection (28 ms) opposed to early detection errors (6 ms). However, the RMS true errors for both gait events remained less than 30ms, with HS and TO events detectable within 4% of the gait cycle in real time.

As depicted in Fig.4, the overall mean of inter-subject variability obtained for HS event was 6 ms, which was comparably less than the mean variability reported for TO (18 ms) event. This may have been due to the fact that signal characteristics of the input parameters (hip angle, hip angular velocity and ankle angular velocity) governing the detection of HS event being more distinct as compared to the TO event, thereby producing minimum uncertainty for HS detection.

Although commonly seen in walking gait analysis, gait event detection for running is seldom reported. Hreljac [4] utilized a 180Hz camera based algorithm for the detection of HS and TO events, which resulted in 2.4ms and 2.8ms TE for HS and TO. Although high detection accuracy was achieved, the instrumentation used for gait event detection may have limitations in terms of cost and the expansion of system use outside the traditional laboratory setting. Furthermore, the detections are identified offline, which lacks the potential for use in real time feedback applications. Lee [10] described the use of sacrum acceleration measurements for the determination of stance phase, stride and step durations during running gait. The timing accuracy was reported to within 20ms, for stance, stride and step durations, however timing errors for HS and TO events was not presented. Nevertheless, the detection has been carried out offline, which limits the use of the system for online gait evaluations and real time feedback.

In this regard, the current approach of using lower extremity kinematic measurements for online running gait event detection is novel, and contributes to the lack of gait event detection studies reported for running. The accuracy of the detection algorithm produced promising results compared to normative event times with minimum timing errors. The use of a FSC eliminated the spurious event detections whilst increasing the reliability and robustness of the detection for online applications. The online running gait event detection system implemented in this study is intended to be used with a real time vibrotactile biofeedback system, to provide immediate corrective feedback for increased hip adduction and ankle pronation orientations during the stance phase of running. The accuracy obtained from the gait event detection highlights the applicability of the developed algorithm for reliable, efficient online event detection that is suitable to be used for the activation of real time feedback during running gait retraining.

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