Application of the ActiGraph GT9X IMU for the Assessment of Turning During Walking and Running

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DEDICATIONS

I dedicate this thesis to my family, friends, and faculty. Thank you to my family for supporting me throughout my life and my decision to pursue a master's degree. And to my friends, thank you for sharing in my successes, making the good times great, and the sleep deprivation study bearable. Thank you faculty members for teaching me so much during my short time at UT. And a special thank you to Susan. Your constant words of appraisal and encouragement kept me up when I was down.

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ABSTRACT

PURPOSE: The purpose of this study was to examine the use of the ActiGraph GT9X gyroscope and magnetometer for turn detection and quantifying turn degree during walking and running. **METHODS:** Participants (N=17) completed pivot trials, treadmill walking and running (3 to 6 mph) and different degrees of turns (i.e. 45°, 90°, 135°, and 180°) during over-ground walking and running. Pivot and walking and running activities were completed for 1-minute and 6-minutes per trial, respectively. Turn frequency was constant (10 turns/minute) across all over-ground walking and running trials. ActiGraph GT9X devices were placed on the left and right hips, wrists, and ankles and a Cosmed K4b^2 measured energy expenditure. Raw ActiGraph GT9X gyroscope and magnetometer data were processed through various low-pass filter frequencies (0.25 Hz to 2.0 Hz). Treadmill and pivot trials were used to develop thresholds for turn detection using gyroscope and magnetometer data. Cross-validation was completed using over-ground trials for turn detection and turn degree using filtered gyroscope data. Cosmed data (VO_2) were averaged over 30-second periods and then converted to relative VO_2 (ml/kg·min) for each activity. Linear mixed models were used to compare actual and predicted number of turns, measured and predicted turn degree, and differences in VO_2 across walking and running speed and turn degree. Linear regression models were used to predict VO_2 using speed, turn degree, and speed and turn degree. **RESULTS:** Greater than 98% of turns were detected when using gyroscope data filtered at 0.25 Hz. Turn degree was estimated within 2.2° of measured turn degree across all speeds. In general, the VO_2 of walking and running increased as the turn degree increased beyond 135°. Walking and running speed explained 83.8% of the variability in VO_2, and the addition of turn degree explained an additional 4.3%. **CONCLUSION:** The ActiGraph GT9X gyroscope, when filtered at 0.25 Hz can be used to detect the number of turns and estimate turn degree. The magnetometer was only useful for detecting the number of turns. Future work is needed to explore the gyroscope application for turn detection performance during activities other than walking and running and estimating VO_2.

Key Words: Energy expenditure, filter, gyroscope, magnetometer, turn degree, turn detection

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CHAPTER I: INTRODUCTION

Research has shown that physical activity (PA) can reduce the risk of premature mortality (47) and prevent the development of chronic diseases such as coronary heart disease (40), diabetes (38), and certain types of cancer (colon and breast) (26). Current aerobic PA guidelines state that U.S. adults should accumulate at least 150 minutes/week of moderate or 75 minutes/week of vigorous intensity PA, or a combination of both (74). However, the proportion of adults who meet the aerobic PA guidelines varies depending on how PA is measured. Based on data from the National Health and Nutrition Examination Survey (NHANES), the proportion of U.S. adults who met the aerobic PA guidelines via self-report questionnaire was 33.5% (10), though that proportion is approximately 5% when estimated using an accelerometer prediction equation (71). Self-report questionnaires are often used in large-epidemiology studies since they are quick and easy to administer. However, they are susceptible to user error (e.g. memory recall), resulting in miscalculated amounts of time spent in PA (67). Accelerometers measure linear accelerations of the body, which can be used to estimate energy expenditure (EE) and time spent in sedentary behavior or different PA intensities (e.g. light, moderate, vigorous). Accelerometers are capable of storing large amounts of data and do not rely on participant memory recall (27). Despite this, EE estimates using accelerometers can vary across devices and methods used to process data (44).

ActiGraph (ActiGraph, Pensacola, FL) devices are the most popular accelerometers used in research (56). ActiGraph accelerometer data are often converted to counts (11), which are used in regression equations for estimating EE (46). Estimates of EE from ActiGraph equations are accurate for activities similar to those that the equations were developed from, but no single equation is valid across all activities and intensities (12). A limitation when using a single ActiGraph device is the inability to capture all human movement. For example, an ActiGraph

worn on the hip can measure general movements of the body but arm movements may go undetected. This will result in an underestimation of EE for most moderate- and vigorous-intensity activities that involve large amounts of upper body movement, such as basketball or tennis (12).

To capture more comprehensive details of movement and improve EE estimates, researchers have explored the application of devices that incorporate multiple sensors. The Sensewear Armband (BodyMedia, Pittsburgh, PA) is a multi-sensor device that consists of an accelerometer and physiological sensors that measure skin temperature, near-body ambient temperature, and galvanic conductivity of the skin (23). The latest Sensewear algorithms are accurate for estimating EE during activities of daily living (ADL) (6, 9, 76) and cycling (8), though are inaccurate for vigorous-intensity activities (17). Thus, the use of multiple sensors has potential to improve estimates of EE compared to using a single sensor.

The latest ActiGraph device (ActiGraph GT9X) is a multi-sensor device that houses an inertial measurement unit (IMU) in addition to the primary accelerometer. The IMU components measure acceleration of the body (secondary accelerometer), angular velocity (gyroscope) and directional heading in reference to Earth's magnetic field (magnetometer). In application, the IMU can be used to quantify rotational motion (e.g. turning), which occurs frequently during everyday life. Studies have shown that turn degree (28, 36, 79) and the frequency of turning (29) while walking or running can significantly influence EE. IMU sensors have been previously examined for determining postural orientation (5), features of walking, running, and jumping (42), and fall risk behavior via walking gait analysis (65). To date, there are no studies examining the ActiGraph GT9X IMU components to identify and quantify turn characteristics or estimate EE.

Statement of the Problem

Previous studies have shown an underestimation of EE during moderate-vigorous intensity activities using accelerometer regressions. Turning movements occur frequently during lifestyle and sporting activities, though accelerometers do not provide measures of angular velocity or changes in direction. Previous studies have shown that changes in turn degree and frequency can significantly influence EE. To improve the quantification of total movement and improve estimates of EE, turning characteristics should be examined. Researchers may benefit from the application of the ActiGraph GT9X gyroscope and magnetometer for detecting turns and quantifying turning characteristics.

Statement of Purpose

The purpose of this study is to examine the use of the ActiGraph GT9X gyroscope and magnetometer for turn detection while walking and running. The second purpose of this study is to examine the use of the gyroscope and magnetometer for capturing turn characteristics (i.e. turn degree). The third purpose of this study is to determine if different turning degrees while walking and running affect EE. The fourth purpose of this study is to determine if gyroscope and magnetometer data correlate with EE across different turning degrees and walking and running speeds.

Research Questions

Question 1: Can the ActiGraph gyroscope and magnetometer be used to detect turns when walking and running?

Hypothesis 1: It is hypothesized that turning while walking and running can be detected using gyroscope data.

Hypothesis 2: It is hypothesized that turning while walking and running can be detected using magnetometer data

Question 2: Can the gyroscope and magnetometer data be used to determine turn degree while walking and running?

Hypothesis 3: It is hypothesized that the gyroscope data will be able to determine turn degree while walking and running.

Hypothesis 4: It is hypothesized that the magnetometer data will be able to determine turn degree while walking and running.

Question 3: Will changes in EE occur across different walking and running speeds and turning degrees?

Hypothesis 5: It is hypothesized that changes in EE will occur across different speeds of locomotion and turning conditions.

Question 4: Will gyroscope and magnetometer data correlate with EE across different turning degrees and walking and running speeds?

Hypothesis 6: It is hypothesized that changes in gyroscope data will correlate with changes in EE across different turning degrees and walking and running speeds

Hypothesis 7: It is hypothesized that changes in magnetometer data will not correlate with changes in EE across different turning degrees and walking and running speeds.

Delimitations

1. Participants shall be between 18-40 years.
2. Participants must answer “No” to all questions on a PAR-Q.
3. Participants will be excluded if they have received surgery or experienced any injury to the lower extremity within the past six months.
4. Activities will be limited to the facilities and equipment available in the HPER building and the Fulton Bottoms Rugby Field on campus.

Limitations

1. Participants will be exposed to some risk inherent to vigorous intensity physical activity, and are asked to answer the PAR-Q truthfully.
2. Excess noise in ActiGraph GT9X data may be observed due to using manufacturer-provided elastic straps and bands as opposed to direct adherence to participant skin.

CHAPTER II: REVIEW OF LITERATURE

Introduction

Research has shown physical activity (PA) to be beneficial for reducing the risk of chronic disease development. Specifically, accumulating higher volumes of PA reduces the risk of coronary heart disease by up to 27% (40), breast cancer by 16% (26), and diabetes by 58% (37). Lee et al. (41) estimate physical inactivity (activity level insufficient to meet PA recommendations) to account for 6-10% of the development of non-communicable diseases and premature mortality worldwide. The authors infer that a reduction in current physical inactivity levels by 6-10% could prevent >533,000 deaths annually.

Health organizations worldwide have established PA recommendations, which outline the recommended amount of PA needed to improve health. Current aerobic PA guidelines state that U.S. adults should accumulate at least 150 minutes/week of moderate or 75 minutes/week of vigorous intensity PA, or a combination of both (74). Though PA guidelines have been established, a majority of the U.S. population does not meet the aerobic PA recommendations. Using self-report data from the 1999 to 2006 National Health and Nutrition Examination Survey (NHANES), Carlson et al. (10) showed that only 34% of U.S. adults met the aerobic PA recommendations. Tucker et al. (73) showed that prevalence estimates of those who meet PA recommendations varies depending on how PA is measured. Analyzing only moderate- and vigorous-intensity PA performed in bouts of at least 10-minutes, the proportion of adults who met the PA guidelines was higher using self-report (62%) compared to estimates using an accelerometer prediction equation (9%).

To achieve more precise estimates of EE and time spent in PA, researchers have explored the use of multiple regression-models, machine learning algorithms, multiple devices

simultaneously, or devices that incorporate multiple sensors. Specific to using more devices or different sensors, more information is available that provides comprehensive information on human movement compared to what can be achieved using a single tri-axial accelerometer. The purpose of this review of literature is to examine how energy expenditure (EE) is estimated and the application of multiple devices or sensors for improving those estimates.

Criterion Methods for Measuring Energy Expenditure

Doubly Labeled Water

Doubly labeled water (DLW) is considered the gold standard for measuring energy expenditure (EE) in free-living conditions. After consuming labeled isotopes of hydrogen (^{2}H) and oxygen (^{18}O), ^{2}H isotopes are expelled from the body as water while the ^{18}O isotopes are expelled as water and carbon dioxide (CO_2). The excess difference between ^{18}O and ^{2}H elimination rates is proportional to CO_2 production and thus can be used to calculate EE. Schoeller et al. (64) compared the measured EE from DLW and a whole-room indirect-calorimeter. Participants stayed in the calorimeter for 22.5 hours/day for four days and performed 68-minute walking bouts on a treadmill two times per day. Results showed that measured daily EE from DLW was within 8% of the whole-room calorimeter. Though DLW can provide accurate measures of daily EE, it is expensive and does not allow for real-time assessment of EE or the duration and intensity of PA bouts.

Direct and Indirect Calorimetry

Direct calorimetry refers to the quantification of EE through the measurement of heat produced from the body while in a whole-room calorimeter. These chambers are used primarily to measure 24-hour total EE, which includes basal metabolic rate, resting EE, individual activities, and thermic effect of food (33). The application of direct calorimeters for measuring

daily EE is limited to activities within the confined space of the calorimeter, which can alter behaviors from daily life. Due to the limitation in activity selection, results are less generalizable to free-living activities.

Indirect calorimetry is commonly used to quantify EE in a laboratory or field setting. The inspired and expired air is sampled to measure oxygen consumption (VO_2) and carbon dioxide production (VCO_2). The difference between inspired and expired O_2 can be used to calculate EE. The Douglas bag method (gold standard for indirect calorimetry) uses large canvas bags to collect expired gases for analysis. Computerized metabolic carts, such as the ParvoMedics TrueOne 2400 (Parvo Medics, Sandy UT), are widely used in laboratory settings and have been validated against the Douglas bag method for measured VO_2 and EE. Bassett et al. (3) compared the measured EE between a ParvoMedics TrueOne 2400 and the Douglas bag method during cycle ergometer activities. On average, cycling VO_2 differences between the ParvoMedics cart and Douglas bag methods were small (0.02 L/min; $p < 0.05$) and negligible in terms of physiological importance. A limitation to computerized metabolic carts, such as the ParvoMedics metabolic cart, is that they are limited to activities performed in a laboratory setting.

The Cosmed K4b^2 (Cosmed, Rome, Italy) is a portable indirect calorimeter that analyzes inspired and expired air breath-by-breath for VO_2 and VCO_2. The Cosmed is lightweight (approximately 800 grams) and consists of a facemask connected to a metabolic unit and battery pack. A manufacturer-designed harness affixes the metabolic unit and a portable battery to the chest and back, respectively. McLaughlin et al. (48) examined the accuracy of the Cosmed K4b^2 compared to the Douglas bag method for measuring VO_2 at rest and during stationary cycling at various intensities ranging from 50 to 250 W. There were no significant differences between the Cosmed and Douglas bag resting VO_2 (0.33 ± 0.02 vs 0.38 ± 0.02 L/min, respectively) and

cycling VO_2 at 250 W (3.51 ± 0.07 vs 3.50 ± 0.05 L/min, respectively; $p < 0.05$). However, differences between the Cosmed and Douglas bag VO_2 were small (< 0.1 L/min; $p < 0.05$) and concluded to be physiologically insignificant, thus making it practical for the assessment of EE in free-living conditions.

Self-Report Questionnaires

Self-report questionnaires can be used to acquire information regarding the frequency, intensity, and duration of habitual PA. Large cohort studies have often used questionnaires to estimate PA since they are low cost and easy to administer to large groups. Questionnaires are more appropriate in the assessment of specific types of PA behavior (e.g. resistance training) and the domain of PA (e.g. occupational or transportation) compared to device-based methods (72). Limitations to using questionnaires include respondent memory recall, social desirability bias, and question misinterpretation (61). For example, light intensity PA is often intermittent and short in duration, which can be difficult to recall and accurately capture via questionnaire (39). Device-based methods, such as accelerometers, provide detailed information on human movement, which can be used to estimate EE.

Accelerometry

Accelerometers measure linear acceleration and deceleration in gravitational units (*unit = g; 1 g = 9.8 m/s^2*). Accelerometer-based devices impose minimal burden due to their compact size, are able to store large amounts of data, and provide time stamped data to determine precise times and durations when movement may have occurred. In a review by Plasqui et al. (56), the ActiGraph (ActiGraph, Pensacola, FL), formerly known as CSA and MTI, was shown to be the most popular and widely used accelerometer device for monitoring PA. The current ActiGraph devices contain a primary tri-axial accelerometer, which can be initialized to sample data

between 30-100 Hz. The raw digital acceleration signal is low-pass filtered to reduce the signal-to-noise ratio. This reduces the signal artifact so that changes in acceleration data are most representative of human movement. Low-pass filtered acceleration data can then be full-wave rectified, thus converting negative data to positive values, and processed with a band-pass filter. The area under the curve is integrated within a user-specified window of time to produce "counts", which are used in ActiGraph regression equations for estimating EE (11).

Freedson et al. (22) was the first to show a high correlation between counts and EE during treadmill walking and jogging ($r = 0.88$) using the CSA accelerometer. Across all treadmill activities, the standard error of the Freedson equation for estimating EE was within 1.40 kcal/min. Since then, other regression models have been developed based on activities in addition to treadmill walking and running. Swartz et al. (70) examined counts collected at the hip and wrist during moderate-intensity lifestyle activities and developed linear regression models to estimate metabolic equivalents (METs). The EE estimates using counts at the hip and wrist were within 1.16 and 1.38 METs, respectively. Crouter et al. (12) examined the validity of regression equations related to three accelerometer devices (ActiGraph 7164, Actical, AMP-331) for estimating EE during activities ranging from sedentary behavior to vigorous intensity. Results showed that no single ActiGraph regression is valid for predicting EE across all activities. However, regressions were most accurate for activities that were used to develop them. Specifically, EE estimates from the Freedson (22) equation were accurate for walking activities and EE estimates from the Swartz (70) equation were accurate for moderate-intensity lifestyle activities, though both overestimated sedentary and light activities and underestimated most other activities.

Crouter et al. (13) observed that walking and running could be distinguished from other activities based on the variability in activity counts between six-consecutive 10-second periods. Thus, they used the coefficient of variation (CV) of counts per 10-second epochs within a one-minute period to identify if an activity was continuous walking and running or an intermittent lifestyle activity. A two-regression model was developed to predict METs for the walk/run and lifestyle activity groups, respectively. Across all activities, the two-regression model predicted EE within 0.75 METs of measured METs, an improvement over previous ActiGraph regressions.

Lyden et al. (46) performed a comprehensive study examining the accuracy of various ActiGraph GT1M, Actical, and RT3 regression equations for predicting EE during treadmill activities and activities of daily living (ADL). Results of the study were similar to those found by Crouter et al. (12). The Freedson equation estimated EE within 1.5 METs and 3.1 METs for treadmill activities and ADL, respectively. The Swartz equation resulted in a smaller error during ADL compared to the Freedson equation (RMSE = 2.6 vs 3.1 METs, respectively), though it mostly underestimated EE during vigorous intensity activities. The error for estimating EE during ADL was reduced using the Crouter two-regression model (13) compared to the Swartz equation (RMSE = 2.3 vs 2.6 METs, respectively), though did not improve estimates for treadmill activities (RMSE = 1.7 vs 1.3 METs, respectively). Across all activities, the Swartz and Crouter models estimated EE within 2.0 METs while the Freedson equation was within 2.3 METs of measured METs.

Crouter et al. (14) compared predicted EE and time spent in sedentary behavior and light, moderate, and vigorous intensity PA to measured EE during free-living conditions using the 2006 Crouter two-regression (13) and 2010 refined Crouter two-regression (15) models and the Matthews and NHANES cut-points. Sedentary behavior and light-, moderate-, and vigorous- PA

were defined as less than 1.5 METs, 1.5-2.9 METs, 3-5.9 METs and greater than 6.0 METs, respectively. Participants were monitored for six-hours during their normal daily routine (e.g. work, leisure time) while wearing an ActiGraph GT1M on the hip and the Cosmed K4b^2. Compared to measured mean METs (1.90 ± 0.68 METs), mean predicted METs was significantly higher using the 2006 Crouter algorithm (2.32 ± 0.84 METs; $p < 0.05$), though the 2010 refined Crouter algorithm (2.08 ± 0.77 METs) was not significantly different from measured METs ($p > 0.05$). Compared to measured time spent in sedentary behavior and PA, the Crouter 2006 underestimated sedentary behavior by 1.8% and overestimated vigorous intensity PA by 163.1% ($p > 0.05$), though time spent in light intensity PA was underestimated by 34.4% and moderate-intensity PA was overestimated by 76.5% ($p < 0.05$). The 2010 refined Crouter algorithm underestimated time spent in sedentary behavior by 20.8% ($p < 0.05$) and overestimated time spent in light- (9.5%), moderate- (44.5%), and vigorous-intensity (62.4%; $p > 0.05$) PA. The NHANES cut-points overestimated time spent in sedentary behavior and light-intensity PA by 9.9% and 8.3%, respectively an underestimated time spent in vigorous-intensity PA by 56.7% ($p > 0.05$). Time spent in moderate-intensity PA was significantly underestimated using the NHANES cut-points by 23.8 minutes ($p < 0.05$). The Matthews cut-points overestimated time spent in sedentary behavior and moderate-intensity PA by 9.9% and 33.4%, respectively and underestimated time spent vigorous-intensity PA by 56.7% ($p > 0.05$). Light intensity PA was significantly underestimated using the Matthews cut-points by 30.2 minutes ($p < 0.05$). Although the 2010 refined Crouter algorithm improved free-living EE estimates compared to the 2006 Crouter algorithm, there was a large discrepancy between measured and estimated time spent in sedentary behavior and moderate- to vigorous-intensity PA. Results

shows that algorithms are inconsistent for estimating time spent in different intensities of PA when applied to free-living PA.

More recent advancements in the use of accelerometer data have been investigated using machine-learning algorithms for classifying activities. Staudenmayer et al. (69) applied an artificial neural network (ANN) to ActiGraph 7164 accelerometer data that were collected during various ADL, locomotion, and sporting activities. Using leave-one-out cross-validation, the ANN correctly classified 88.8 ± 2.4% of activities. For minute-by-minute estimates of METs, the ANN was within 1.22 METs of measured METs, which reduced the EE estimation error compared to the Crouter two-regression model (13) (RMSE = 1.61 METs). Machine-learning algorithms can improve estimates of EE compared to simpler regression models, though the use of a single accelerometer alone does not capture all human movement.

Integration of Multiple Devices and Sensors

In a review of micro-sensors for the assessment of body motion and movement, Zeng et al. (80) states that the integration and coordination of multiple devices or using a single device with multiple sensors will lead to the greatest success for quantifying and interpreting total body movement.

Intelligent Device for Energy Expenditure and Activity

The Intelligent Device for Energy Expenditure and Activity (IDEEA; MiniSun LLC, Fresno, CA) is a multi-device system that records body motion for determining postural orientation and activity classification (81). The IDEEA consists of a recording unit mounted on the waist that is connected to five accelerometers adhered to the skin at different anatomical locations (i.e. sternum, anterior thighs, and plantar surface of both feet).

Zhang et al. (81) compared IDEEA algorithm EE estimates to measured EE from indirect calorimetry. During the first visit, participants performed a structured set of tasks comprised of walking, running and different postural orientations (i.e. sitting, standing, lying down). For the second visit, participants were placed in a calorimeter chamber for 23-hours. During the 23-hour period, participants performed three separate sessions of treadmill walking or running. IDEEA algorithm estimates of EE for structured and unstructured activities performed in the calorimeter were within 98.9 ± 6.0% and 95.2 ± 2.3% of measured EE, respectively. A limitation identified by the researchers was the IDEEA's inability to identify arm movement, which could result in an underestimation of EE during certain activities.

Whybrow et al. (77) compared IDEEA algorithm EE estimates to whole-room indirect-calorimetry and DLW during structured and free-living activities. The protocol in the calorimeter was similar to Zhang et al. (81), though additional postural orientations, step tests, and cycle ergometer activities were included. Compared to measured EE, the IDEEA underestimated EE by -0.9 ± 0.74 MJ ($p<0.001$) across all structured activities, but overestimated EE by 1.25 ± 0.73 MJ ($p<0.001$) when cycling activities were excluded. The IDEEA overestimated TDEE by 2.61 ± 1.10 MJ ($p < 0.001$) during the free-living period. The IDEEA estimates of EE were within 99.7 ± 7.3% of measured EE for calorimeter activities, which are similar to the results of Zhang et al. (81).

Dannecker et al. (16) compared EE estimation accuracy for the Actical (Phillips Respironics Inc., Bend, OR) algorithm based on Heil et al. (30), ActiGraph GT3X (Freedson (22)), IDEEA, and a proprietary shoe-mounted accelerometer. Participants completed a four-hour stay in a whole-room indirect calorimeter where they performed sitting, standing, treadmill walking, cycling, and moderate-intensity (i.e. stepping, sweeping) lifestyle activities. Regression

estimates of EE across all activities were within 19% (Actical), 27% (ActiGraph Freedson equation), and 18% (IDEEA) compared to measured EE. EE estimation error was reduced across the activities measured using the IDEEA algorithm compared to the ActiGraph Freedson equation.

Wireless Accelerometer Network

Montoye et al. (49) examined the accuracy of a wireless accelerometer network for predicting EE during sedentary behaviors (lying down and sitting), treadmill walking and running, lifestyle activities (standing, sweeping, stair climbing), and exercise (bicep curls, cycling, squatting, jumping jacks). Participants wore an ActiGraph GT3X+ on the hip and the wireless accelerometer network comprised of three wireless MICA2DOT motes (Crossbow Inc., Milpitas, CA, USA) on the right wrist, thigh, and ankle. ANNs were created separately for the ActiGraph GT3X+ and wireless network using means and standard deviations of each axis. Across all activities, predicted METs were not significantly different between ANNs for the ActiGraph GT3X+ (RMSE = 2.09 ± 0.28 METs) and wireless accelerometer network (2.16 ± 0.36; $p > 0.05$). Results show that similar EE estimates can be achieved using a single accelerometer or multiple accelerometers.

Sensewear Armband

The Sensewear Armband (BodyMedia, Pittsburgh, PA) is an accelerometer-based multi-sensor device that is worn over the triceps of the right arm. In addition to a 2-axis accelerometer in the Sensewear Pro or 3-axis in the Sensewear Mini, these devices incorporate additional sensors that measure heat flux, galvanic skin response, skin temperature, and near-body temperature. The inclusion of additional sensors to provide information on physiological variables has the potential to improve estimates of EE over a stand-alone accelerometer.

BodyMedia has developed multiple Sensewear devices and released updates to the proprietary software meant to improve its estimates of EE.

Welk et al. (76) examined the Sensewear Pro2 and the ActiGraph (MTI model) accelerometer algorithms for estimating EE during free-living conditions. Participants wore the IDEEA, Sensewear Pro2, and ActiGraph devices for one day. The IDEEA classified the primary activity performed each minute, which consisted of lying supine, sitting, standing, and walking. Sensewear Pro2 software versions 3.9 (SPv1) and 4.1 (SPv2) and six MTI algorithms consisting of one based on the work energy theorem, the Freedson (22) equation, a combination of the work-energy theorem and Freedson equation, the Hendelman (31) walking- and lifestyle-based equations, and the Swartz (70) lifestyle-based equation were used to estimate EE. Across all activities, the average estimated METs from the IDEEA algorithm was 2.04 ± 0.42 METs. Compared to the IDEEA, estimates of EE were within 0.12 METs ($p < 0.05$) for SPv1 and 0.01 METs ($p > 0.05$) for SPv2. EE estimates for ActiGraph algorithms ranged from 1.61 to 3.14 METs. The Swartz equation significantly overestimated EE by 0.93 METs ($p < 0.05$) and the Freedson equation underestimated EE by 0.38 METs ($p >0.05$). Results show EE estimates were improved using the newer Sensewear algorithm (SPv2) compared to SPv1 and SPv2 performed better than the MTI algorithms.

Calabro et al. (9) examined the validity of the ActiGraph GT3X (work energy theorem and Freedson (22) equation), Sensewear Pro3 (software version 6.1, algorithm v2.2.3) and Mini (software version 7.0, algorithm v2.2.4) armbands, ActivPal, and Actiheart Monitor (Cambridge Nurotechnology, Cambridge, UK; software version 4.0.3.2) algorithms for estimating EE during sedentary behaviors and light and moderate intensity activities. For the ActiGraph, the work energy theorem was applied if counts/min < 1952 and the Freedson equation was applied if

counts/min ≥ 1952 to estimate EE. The unstructured activities consisted of sitting, walking, standing, stair ascent and descent, and light-intensity movements. The ActiGraph equations and ActivPal significantly underestimated EE compared to indirect calorimetry EE (25.5% and 22.2%, respectively; $p < 0.05$), while the Sensewear Mini and Pro3 overestimated EE (1% and 4%, respectively; $p > 0.05$). Compared to algorithms that only use accelerometer data, the Sensewear devices produced closer estimates of EE across the measured activities.

Energy Cost of Treadmill and Over-ground Walking and Running

Pugh et al. (57) compared the oxygen cost of running at a self-selected pace on a track and treadmill to observe the impact of air resistance on EE. Participants ran four laps around a track and expired gases were collected via the Douglas bag method during the final lap. The VO_2 of running at 21.5 km/hr on a track (74.6 ml/kg·min) was higher compared to the same speed on a treadmill (68.3 ml/kg·min). Thus, they estimated that 8% of the energy requirement when running over-ground at 21.5 km/hr is attributed to overcoming air resistance. The increase in VO_2 for over-ground running was estimated to be even greater for 100m sprints (approximately 16%).

To account for differences in VO_2 between treadmill and over-ground running at a given speed, Jones et al. (35) compared the VO_2 of running on a treadmill and over-ground at different speeds. Participants completed treadmill and over-ground running trials at six speeds (2.92, 3.33, 3,75, 4.17, 4.58, and 5.0 m/s) for each condition. For treadmill running, five trials with different grades (0%, 0.5%, 1%, 2%, 3%) were completed at each speed. For over-ground running, researchers monitored the pace with a bicycle computer by cycling alongside participants. Measured speeds of participants were within -0.06 m/s of desired speeds. Compared to over-ground running, the VO_2 for treadmill running with a 0% grade was significantly lower by 2.7 ±

0.6 ml/kg·min for 3.75 m/s, 3.2 ± 0.3 ml/kg·min for 4.17 m/s, and 2.7 ± 0.3 ml/kg·min for 4.58 m/s ($p < 0.05$). For all speeds, the VO_2 for treadmill running with a 1% grade was not significantly different from over-ground running ($p > 0.05$). The VO_2 of treadmill running with a 2% grade was significantly higher than over-ground running by 2.7 ± 0.4 ml/kg·min at 3.33 m/s and 2.4 ± 0.6 ml/kg·min at 3.75 m/s ($p < 0.05$). With the exception of 5 m/s, the VO_2 of treadmill running with a 3% grade was significantly higher than over-ground running by up to 5.2 ml/kg·min across all speeds ($p < 0.05$). The authors concluded that treadmill running with a 1% grade was most similar to over-ground running for running speeds examined.

Energy Requirement of Running on Different Surfaces

Sassi et al. (62) measured the shock absorption characteristics of asphalt, natural grass, and artificial turf and compared the VO_2 of running at 2.22, 2.8, and 3.33 m/s on each surface. The shock absorption proportion of asphalt (1.0 ± 2.1%) was significantly different from natural grass (34.5 ± 2.7%) and artificial turf (37.7 ± 2.5%; $p < 0.05$). Results showed a significant main effect of surface ($p < 0.004$) and speed ($p < 0.001$) on VO_2. Running VO_2 was up to 0.2 L/min lower on asphalt compared to grass or artificial turf. Shock absorption characteristics of the ground may explain differences in running VO_2 across different surfaces, though the differences reported in the study are physiologically insignificant.

Turning and Energy Expenditure

Turning is a part of normal everyday activities and is regularly performed in ADL and various sporting activities. For example, turning movements have been reported to account for 35-50% of steps during simulated ADL (25) and are commonly observed during kitchen activities (e.g. cooking, dishwashing), cleaning (e.g. vacuuming, dusting), or navigating corners while walking. Sports such as tennis and soccer also incorporate frequent turning movements

that are more dynamic in turn rate and degree compared to turning during ADL. Studies examining match play characteristics among Football Association (FA) Premier League soccer players have found that players execute 727 ± 203 purposeful turns (7.8 ± 2.3 turns/min) during match play with most turns performed within the range of 0° to 90° (7). In a video analysis of match gameplay among junior tennis players, 2.3 ± 1.4 changes in direction occurred during a given rally, with each rally lasting on average 8.2 ± 5.2s (21).

When greater turn degrees are performed during running, momentum is controlled throughout the turn by an initial deceleration phase prior to the change in direction, followed by the tilt of the trunk towards the intended change of direction, and rapid acceleration in the new heading (32). Ventura et al. (75) examined the difference in lower extremity muscle-activation patterns between straight-line walking and walking along a curved path (clockwise and counter-clockwise) at a self-selected pace. Force plates and 3D-motion capture were used to collect kinematic data and computerized musculoskeletal models determined muscle excitation. Muscles analyzed in the musculoskeletal model included the iliacus; gluteus medius and maximus; adductors; sartorius; hamstrings; rectus femoris; vastus intermedius, lateralis, and medialis; gastrocnemius; soleus; and tibialis posterior and anterior. Muscle contribution to changes in center of mass and angular accelerations were determined using the impulses derived from the musculoskeletal model. Compared to straight-line walking, the impulse of the gluteus medius, tibialis posterior, adductors, soleus, and gastrocnemius muscle groups were significantly different for walking along a curved-path ($p < 0.05$). This indicated that those muscles contributed to the redirection of the center of mass acceleration towards the mediolateral direction. Impulses for the adductor, gluteus medius, gluteus maximus, and iliacus muscle groups significantly contributed to pelvic angular acceleration to rotate the pelvis internal towards the

center of the turn ($p < 0.05$). The increased muscle impulse helps to maintain body stability throughout the turn while walking. As a result, the increased muscle activation of turning during walking may potentially increase EE compared to straight-line walking.

General characteristics of turning, such as turn degree, frequency, or walking and running speed, can significantly increase EE. Hatamoto et al. (28) compared the VO_2 of walking (4.3 km/hr) and running (5.4 km/hr) while performing 180° turns for ten participants. At each speed, participants completed five trials consisting of different turn frequencies ranging from 8 to 30 turns/minute. The VO_2 of a turn was estimated as the slope of a linear regression between turn frequency and walking/running VO_2. A strong correlation was observed between turn frequency and VO_2 for 4.3 km/hr ($r = 0.973$) and 5.4 km/hr ($r = 0.996$). The average VO_2 of a turn was significantly different between the 4.3 km/hr (0.34 mL/kg ± 0.13) and 5.4 km/hr (0.55 ± 0.09 mL/kg; $p < 0.001$) speeds. The authors speculate that faster running speeds required greater acceleration and deceleration rates to perform a 180° turn while higher turn frequencies led to greater proportion of time spent in acceleration and deceleration phases. A limitation to the studies by Hatamoto et al. is that they only examined turns of 180°, thus the impact of other degrees of turning on EE needs to be examined.

Inertial Measurement Unit

An inertial measurement unit (IMU) is comprised of a triaxial accelerometer (linear acceleration), gyroscope (angular velocity), and magnetometer (directional heading in relation to Earth's magnetic field). An IMU is often used in navigation systems (63), though has received growing interest for the assessment of human movement such as gait analysis (65), postural orientation (45), and fall risk prevention (24) . The gyroscope and magnetometer components

have also been used to detect turns and quantify turning characteristics (53, 55, 68), though there are limited studies that examine their application for estimating EE.

Ayachi et al. (2) used multiple IMUs to develop an algorithm to detect and classify various movements commonly performed during ADL in older adults. Movements performed consisted of stand-up, sit-down, walking, bending down, stepping over objects, reaching up or down, and turning left or right. During all movements participants wore a Synertial suit (Synertial UK Ltd IGS-180), which is comprised of 17 IMU modules affixed at different locations on the body (head; upper-, mid-, and lower- spine; upper and lower arms; wrists; lateral thighs; calves, and ankles) to capture full body kinematics. Specific IMU module locations were used to identify different movements. For example, the IMU module affixed to the thigh was used to identify turns to the left or right using the angular velocity about the Y-axis. Of the total tasks performed (n = 1999), 97.5% of all movements, including 94.74% of turns to the left and 93.77% of turns to the right, were correctly identified. Though numerous IMU devices were worn during all activities, results show that a single IMU can be used to correctly identify specific movements with up to 98% classification accuracy.

Gyroscope

Shoaib et al. (66) examined the application of an accelerometer and gyroscope within a smartphone for activity classification. Activities performed consisted of standing, sitting, walking, jogging, biking, and stair ascent and descent. Smartphones were affixed to the upper right arm, hip, right wrist, and were placed inside the pants pockets during all activities. The smartphone on the right wrist was meant to simulate data similar to a wrist-worn activity monitor. Accelerometer and gyroscope features used in machine learning algorithms to classify activities consisted of mean, standard deviation, median, variance, zero crossing, root mean

square, fast Fourier transformation coefficients, and signal spectral energy. Classification accuracies of standing and sitting activities were greater than 95% for the hip, wrist, and pocket locations using the accelerometer, which improved classification accuracy compared to using the gyroscope alone by 14.7 to 41.1%. Classification accuracy of stair ascent and descent was 80 to 85% using the accelerometer, which was lower than using the gyroscope by 3.8 to 11.9%. Walking and stair ascent and descent classification accuracy was improved by 5.1 to 14.1% using the combination of accelerometer and gyroscope data compared to using either sensor alone.

Lee et al. (42) examined signal features from an accelerometer (ADXL345, Analog Device, MA, USA) and gyroscope (MPY3050, InvenSense, CA, USA) for the assessment of slow and fast walking, slow and fast running, and low and high jumping (30% and 100% of max jump effort, respectively). Sensors were placed on the outside of the left shoe during all activities. Five-consecutive gait cycles during walking and running and one jump for jumping activities were used for analysis. The Pythagorean theorem was used to calculate resultant acceleration vectors using a combination of two axes (XY, XZ, and YZ axes) and all three axes (XYZ). Averages for accelerometer data were calculated for each axis and resultant vectors. Maximum and minimum angular velocities for each axis were compared across activities for gyroscope data. Analysis of the tri-axial accelerometer and gyroscope showed that with the exception of acceleration in the anteroposterior direction, there was a significant interaction between intensity and locomotion ($p < 0.01$). Specifically, the peak Y-axis gyroscope angular velocities for walking at a 1.0 m/s and 2.0 m/s were 776.31 ± 52.67 deg/sec compared to 1139.67 ± 75.18 deg/sec, respectively ($p<0.01$). Peak angular velocity about the Y-axis for running at 2.0 m/s and 3.5 m/s were 817.53 ± 64.19 deg/sec and 1258.28 ± 78.95 deg/sec, respectively ($p <$

0.01). Angular velocity about the Y-axis for 30% of max and maximal jumps were 884.62 ± 77.80 deg/sec and 961.58 ± 123.90 deg/sec, respectively ($p < 0.01$). The authors conclude that acceleration and angular velocity variability may be useful for distinguishing between intensity levels within specific activities and should be considered to improve activity identification.

Novak et al. (53) examined the application of IMUs at various anatomical locations (head, upper/lower back, thigh, shank, and foot) to determine the optimal placement for real-time detection and quantification of turns during self-selected walking speeds. Before each trial, participants were instructed to either walk straight or perform a 22°, 45°, or 90° turn to the right or left. Algorithms were developed using thresholds from the angular velocity or angle orientation around the Y-axis axis, or a combination of the two, to identify the start and stop of turns and classify the direction (right or left) and degree (22°, 45°, 90°) of turns. Turn start and stop times and the degree of turns were validated against 3-D motion capture and were considered correctly detected if the estimated start of a turn occurred within 500 ms of the criterion. Only turns that were correctly identified were included for turn direction and degree analysis. IMU devices affixed to the back were most accurate for turn detection, thus results for the lower back are reported. Turn onset accuracy was similar between algorithms using angular velocity (74.3%) and angle orientation (68.7%) thresholds, though was improved when using a combination of the two (77.3%). Turn direction to the left or right was correctly identified for over 95% of cases across all turning conditions. Turn degree classification accuracy ranged from 45 to 80%, though the majority of misclassification occurred between 22- and 45- degree turns. Thus, the authors conclude that the optimal IMU placement is at the upper or lower back and a combination of both angular velocity and angle orientation thresholds produced the greatest accuracy for turn onset detection.

Wundersitz et al. (78) evaluated the activity classification performance of an accelerometer and gyroscope placed at the base of the neck (MinimaxX S4, Catapult Innovations, Australia). Activities performed were comprised of those related to team-sport movements (i.e. walking, running, changing direction, jumping). Accelerometer (X, Y, Z, Vector Magnitude) and gyroscope (X, Y, Z) data were processed using three different time windows (0.5, 1.0, 1.5 sec) with a 50% overlap for each method. Signal features based on the time domain (amplitude minimum, maximum, mean, variance, 25^{th} percentile, 75^{th} percentile, interquartile range), frequency domain, and custom energy features were calculated for each method. Logistic model tree, support vector machine, and random forest machine learning algorithms were developed using leave-one-out-cross validation to classify activities. The logistic model tree performed the best of the three algorithms with classification rates of 79% or higher across all activities, thus results reported are specific to the logistic model. Differences between classification accuracy using 0.5, 1.0, or 1.5 second windows for feature extraction were less than 1%. Activity classification accuracy was improved using both accelerometer and gyroscope data (92 ± 0.4%) compared to using the accelerometer (88 ± 0.4%) or gyroscope (80 ± 0.8%) alone.

Parkka et al. (54) examined the application of accelerometers and gyroscopes worn at various locations on the body (i.e. hip, wrist, ankle) for estimating EE during ADL. Activities performed consisted of hanging, ironing, and folding laundry, vacuuming, stair ascent and descent, pushing a shopping cart, carrying bags, over-ground walking and running at a self-selected pace, cycling on a cycle ergometer (65% of estimated VO_2 max), and treadmill walking or running (35%, 45%, 55%, 65%, 75%, and 85% of estimated VO_2 max). Cycle ergometer resistance and treadmill speeds specific to each participant were calculated based on VO_2max

estimates taken from a table of normative values specific to age and sex. For each individual axis of accelerometer and gyroscope data, the absolute value of data were taken and the area under the curve was integrated across 30-second intervals to compute the integral-method approach total value (IMAtot). MET estimates were calculated using a linear regression fit on the accelerometer and gyroscope IMAtot and measured METs. Mean MET estimates using accelerometer hip, wrist, and ankle data were within 1.42, 1.40, and 1.21 METs of measured METs, respectively. MET estimates using gyroscope hip, wrist, and ankle data were within 1.71, 2.09, and 1.32 METs of measured METs, respectively The authors conclude that MET estimates using data collected at the ankle was more accurate than the hip and wrist since the majority of their tasks involved mostly lower body movements.

Magnetometer

The majority of research involving IMU devices pertains to the use of the accelerometer and gyroscope components, though few studies have reported the use of the magnetometer for measuring human movement. When included, the magnetometer is often coupled with either the accelerometer and/or gyroscope to improve predictive accuracy of algorithms.

Leuenberger et al. (43) developed an algorithm using a ReSense IMU on the right hip to count the number of 90°, 180°, 270°, and 360° turns a person completed during a predetermined walking route. Raw tri-axial accelerometer, gyroscope, and magnetometer from the ReSense were used to estimate the device orientation relative to the global frame and the participant's orientation angle around the Y-axis. Sensor bias was estimated using static trials for six different orientations, 360° rotation of the ReSense about each axis on a level surface, and freely rotating the cube in space. Sensor data was calibrated using the estimated sensor bias. The authors tested four algorithms comprised of the following: 1) calibrated accelerometer, gyroscope, and

magnetometer data; 2) calibrated accelerometer and gyroscope data; 3) uncalibrated raw accelerometer and gyroscope data; and 4) accelerometer and magnetometer data coupled with an orientation filter. Lower turn count percent errors were achieved from algorithms using calibrated data (1 and 2) and were significantly different from algorithms using uncalibrated data (3 and 4) ($p < 0.05$). Mean turn count percent error was lowest using algorithm 1 for 90° (13.9 ± 5.5%), 180° (6.7 ± 3.3%), 270° (24.29 ± 6.0), and 360° (1.10 ± 2.91%) turns. Compared to algorithm 1, mean turn count percent error was higher using algorithm 2 for 90° (14.29 ± 6.05%), 180° (7.62 ± 3.71%), 270° (8.27 ± 4.14%) and 360° (1.10 ± 2.91%; $p > 0.05$) turns. The turn count percent errors for algorithm 3 and 4 were up to 32.97% and 38.46% higher than algorithm 1, respectively ($p < 0.05$). Thus, the authors conclude that magnetometer data does not significantly improve measurement accuracy, and it may be preferable to omit it from algorithms to improve robustness across environments with varying magnetic field disturbances.

CHAPTER III: MANUSCRIPT

Introduction

Regular physical activity (PA) has been shown to improve health and reduce the risk of chronic disease development (26, 38, 40). Current aerobic PA guidelines state that U.S. adults should accumulate at least 150 minutes/week of moderate or 75 minutes/week of vigorous intensity PA, or a combination of both (74). The proportion of U.S. adults who meet the aerobic PA recommendation can vary depending on how PA is measured. The proportion of adults who meet the aerobic PA recommendation using self-report questionnaire is approximately 33.5% (10), though this proportion is 5% when using an accelerometer prediction equation (71). Self-report questionnaires are often used since they are quick and easy to administer though they rely on respondent memory recall, which can result in miscalculated amounts of time spent in PA (67).

Accelerometers are objective tools that measure linear accelerations of the body, which can be used to estimate energy expenditure (EE). The ActiGraph (ActiGraph, Pensacola, FL) is the most popular and widely used accelerometer in research (56). ActiGraph accelerometer data are often converted to counts (11), which are used in regression equations to estimate EE. Estimates of EE from ActiGraph equations are accurate for activities similar to those that the equations were developed from, but no single equation is valid across all activities and intensities (12). A limitation when using a single ActiGraph device is the inability to capture all human movement.

To achieve more precise estimates of EE, researchers have explored the use of devices with multiple sensors to provide more comprehensive details of total movement. The Sensewear Armband (BodyMedia, Pittsburgh, PA) is a device that includes multiple sensors in addition to

an accelerometer that measure skin temperature, galvanic conductivity of the skin, and near-body ambient temperature (23). It has been shown to improve estimates of EE during activities of daily living (ADL) (6, 9, 76) and cycling (8) compared to algorithms that use only accelerometer data, though is inaccurate for vigorous-intensity activities (17). Thus, the use of multiple sensors has potential to improve estimates of EE compared to using a single sensor.

The latest ActiGraph device (ActiGraphGT9X) is a multi-sensor device that incorporates an inertial measurement unit (IMU). In addition to the primary accelerometer of the ActiGraph GT9X, the IMU components measure acceleration of the body (secondary accelerometer), angular velocity (gyroscope), and directional heading in reference to Earth's magnetic field (magnetometer). In application, the IMU can be used to quantify rotational motion (e.g. turning) via the gyroscope and magnetometer. Turning is a characteristic of human movement that is commonly performed in a number of lifestyle and sporting activities, such as soccer and tennis (4). Previous studies have shown that turning during walking or running can significantly increase EE as turn degree (28, 36, 79) or frequency of turning (29) increases. IMU's have been previously examined for determining postural orientation (5), features of walking, running, and jumping (42), and fall risk behavior via walking gait analysis (65). To date, there are no studies examining the ActiGraph GT9X IMU components to identify and quantify turn characteristics or estimate EE.

The primary purpose of this study was to determine if the gyroscope and magnetometer in the ActiGraph GT9X could be used for turn detection during walking and running. The second purpose of this study was to examine the use of the gyroscope and magnetometer for capturing turn characteristics (i.e. turn degree). The third purpose of this study was to see if turns of varying degrees across walking and running speeds affect EE. The fourth purpose of this study

was to determine if gyroscope and magnetometer data correlate with changes in EE across different turning conditions.

Methods

Participants

A total of 20 participants volunteered to participate in the study. Participants were recruited via word of mouth and flyer distribution at the University of Tennessee, Knoxville and surrounding area. Participants were excluded if they had contraindications to exercise, body-mass index (BMI) greater than or equal to 30 kg/m^2, estimated VO_{2max} less than or equal to 40 $ml/kg \cdot min$, or experienced any injuries or past surgeries to the lower extremities within the past six months. The procedures were reviewed and approved by the Institutional Review Board at The University of Tennessee, Knoxville prior to the start of the study.

Procedures

The study consisted of three sessions completed on separate days. Table 1 outlines a sample protocol of what a participant would complete each day.

Day 1

All activities during day 1 were performed at the Applied Physiology Laboratory on the university campus. Participant height and weight were measured using a stadiometer and calibrated weight scale, respectively, while dressed in light clothing without shoes. Participants were asked to rate their typical PA behavior on a scale of zero to seven (0 = avoids walking or physical exertion, 7 = runs over 10 miles/week or spends 3 hours in comparable PA). To ensure each participant's aerobic fitness was sufficient to complete all trials, a prediction equation was used to estimate VO_{2max} based on age, BMI, PA behavior rating, and gender (34). Participants

were fitted with a portable metabolic measurement system (Cosmed K4b^2) and ActiGraph GT9X devices were affixed to left and right hips, wrists, and ankles using manufacturer-provided elastic bands or straps designed for specific body locations. Participants then completed: 1) postural orientation (i.e. standing, sitting, laying supine, and laying on the side) for 1-min in each position, 2) four pivot trials (i.e. 45°, 90°, 135°, and 180°) for 1-min in each condition, and 3) treadmill walking (3 and 4 mph) and running (5 and 6 mph) for 6-min at each speed.

For pivot trials, participants were instructed to pivot the same number of degrees back and forth between a reference point (0°) and measured angle (Figure 1). Participants were allowed to decide which direction pivots were completed (left or right) and all pivot trials had to be completed in the same direction. A metronome was set to 60 beats/min to help participants maintain a pace of one pivot movement every six beats, resulting in 10 pivots per trial. For the treadmill running, a 1% grade was added to account for differences in wind resistance and surface type that may impact EE during the over-ground running trials (57, 62). A 1- to 3-minute break was allowed between walking and running trials for rest and adjustment of equipment if needed.

Days 2 and 3

Activities for days 2 and 3 were performed at a grass-turf rugby field on the university campus. Participants were equipped with the K4b^2 and GT9X monitors at the same positions as day 1. Participants were randomly assigned one walking (3 mph or 4 mph) and one running (5 mph or 6 mph) speed to be performed during Day 2. The other walking and running speeds were completed on day 3. For each speed, four turning trials (i.e., 45°, 90°, 135°, 180°) were completed for six minutes each and the order of turning degree trials were randomized within each speed. Turns were completed in the same direction that was selected for the pivot trials.

For each condition, participants were instructed to walk and run along marked paths that had cone markers placed at the midpoints and turns (Figure 2). The distances between turns were: 8 m (3 mph), 10.67 m (4 mph), 13.33 m (5 mph), and 16 m (6 mph). A metronome was set to 60 beats/min and participants were instructed to arrive at a cone every three beats, which resulted in a turn occurring every six beats (10 turns/min). Ten turns/min is similar to what may be experienced during sport gameplay (4, 7, 20). If the elapsed time between cones was more than ±1 metronome beats of the expected pace, participants were prompted to speed up or slow down accordingly. If participants failed to adjust their pace within passing two cones, the trial was stopped and repeated after a 1- to 3- minute break.

ActiGraph GT9X

The ActiGraph GT9X is a small (3.5 x 3.5 x 1 cm), lightweight (14 grams), water-resistant device that records and stores raw acceleration (primary accelerometer) data. The primary accelerometer can be initialized to sample between 30-100 Hz and measures accelerations in the dynamic range of ± 8 G's. The primary accelerometer was initialized to sample at 90 Hz. The ActiGraph GT9X also contains an IMU that records and stores raw acceleration (secondary accelerometer), angular velocity (gyroscope), and directional heading (magnetometer). The IMU samples at 100 Hz and the dynamic range for the secondary accelerometer, gyroscope, and magnetometer are ± 16 G's, ± 2000 deg/sec, and ± 4800 μTesla, respectively.

Cosmed K4b^2

The K4b^2 was used to measure oxygen consumption (VO_2) and carbon dioxide production (VCO_2). It consists of a facemask, battery pack, and metabolic unit weighing about

500 grams. A manufacturer-provided harness was worn to affix the battery pack and metabolic unit to the back and chest, respectively. The facemask covers the nose and mouth and contains a turbine to measure airflow. The unit was warmed-up prior to data collection for at least 45 minutes followed by a calibration protocol according to manufacturer guidelines. This consisted of a room air calibration, a reference gas calibration with known concentrations of O_2 (15.98%) and CO_2 (4.008%), and turbine flow calibration using a 3-liter Hans Rudolf syringe. Last, a gas delay calibration was performed to account for delay between the flowmeter and the gas analyzers.

Data Processing

Raw gyroscope and magnetometer data were downloaded from the GT9X IMU using ActiGraph's Actilife software. Gyroscope and magnetometer data from the right hip were processed using MATLAB version R2016a software (Mathworks, Inc. Natick, Massachusetts).

K4b^2 VO_2 (mL/min) data were averaged into 30-second time periods then converted into relative VO_2 (mL/kg·min). An additional 2.0 kg was added to each participant's bodyweight to account for the weight of the devices. The 30-second VO_2 measures for minutes 3-5 for each trial were averaged and used for analysis.

Turn Detection

Separate algorithms for turn detection were developed for the gyroscope and magnetometer using the Y-axis from each sensor. Based on previous literature, it is unclear what low-pass filter should be used for the gyroscope and magnetometer data. Previous studies that examined turning have used low-pass filters between 0.7-1.5 Hz (18, 51, 52). Thus, for the current study, the data were filtered with a second-order low-pass Butterworth filter at various frequencies (0.25, 0.50, 0.75, 1.00, 1.25, 1.50, 1.75, 2.00 Hz). Figure 3 shows the effect of low-

pass filtering (0.25, 0.50, and 2.00 Hz) the raw gyroscope Y-axis for the 90° turn condition at 3 mph. For the gyroscope, filtered angular velocity (ω) data were full-wave rectified. For the magnetometer, the first derivative was taken to calculate the instantaneous rate of change (μT') and then data were full-wave rectified.

Using the treadmill and pivot trials, cut-points to detect when a turn occurs were developed using receiver operating characteristic (ROC) curve analysis. For the ROC analysis, all peaks were identified for ω and μT' within a 30-second window for each treadmill (4 min 15 sec to 4 min 45 sec) and pivot (15 sec to 45 sec) trial (Figure 4). Since one pivot movement was completed every six seconds, five pivot movements were included within the 30-second window for pivot trials. The five greatest ω and μT' peaks from each treadmill and pivot trial were used for analysis. The ROC curves for the gyroscope (Figure 5) and magnetometer (Figure 6) were developed by coding the treadmill peaks (no turn) as zero and pivot peaks (turning) as one. Cross-validation of thresholds for turn detection was carried out using minute four of the over-ground walking and running trials. A turn was considered detected when a local maximum (peak) in ω or μT' occurred above the established thresholds.

Turn Degree

Gyroscope data during minute 4 of the over-ground walking and running trials were used to predict turn degree. The magnetometer can be converted to cardinal direction using a scale published by ActiGraph (Table 2) (1), however the data did not align with the scale for reliable indication of directional heading. Thus, only gyroscope data was used to predict turn degree.

Based on the cross-validation, gyroscope data was filtered using the low-pass frequency that was best for detecting greater than 98% of turns across all speeds and turn degrees and no main effects for speed or turn degree. For each turn detected during the over-ground trials, the

timestamp was used as a reference point to determine the beginning and end of a turn. Turn start and stop times were identified as the timestamps before and after the reference point when ω was less than 5 deg/sec as this threshold has been used in previous work (18). Turn degree was predicted for each turn by using trapezoidal integration to integrate the area under the curve between turn start to stop times (Figure 7).

Statistical Treatment

All statistical analyses were carried out using IBM SPSS statistical software version 24.0 (IBM, Armonk, NY). For all analyses, an alpha level of 0.05 was used to denote statistical significance. All data are presented as mean ± standard deviation, unless noted otherwise.

Number of turns detected was performed for each filtering approach separately. Percent of turns detected (predicted number of turns/actual number of turns*100) were calculated for the gyroscope and magnetometer data. For each filtering frequency, linear mixed models were used to determine main effects and interaction for speed and turn degree on percent of turns detected.

Turn degree error (estimated turn degree minus measured turn degree) was calculated for all turns detected using the gyroscope. A linear mixed-model was also used to compare the turn degree error score to zero. Significant differences were identified when zero was not contained within the 95% confidence interval for estimated turn degree error.

A linear mixed-model was used to determine main effects and interaction for speed and turn degree on VO_2 of the walking and running turning conditions. For significant main effects, pairwise comparisons with Bonferoni adjustments were used to indicate significant differences in VO_2 between the walking and running speeds and turn degree. Linear regression models to predict VO_2 were developed using: 1) walking and running speed only, 2) predicted turn degree only, and 3) walking and running speed and predicted turn degree.

Results

Three participants were excluded from participation in the study due to not meeting the estimated VO_{2max} eligibility criteria (≥40 ml/kg·min). Descriptive statistics of participants included in the analyses are shown in Table 3.

Turn Detection

Tables 4 and 5 show the thresholds for detecting a turn, sensitivity, specificity, and area under the curve, based on the ROC analyses, for each gyroscope and magnetometer low-pass filter frequency. For the gyroscope data, using the 0.25 Hz low-pass filter resulted in a turn detection threshold of 12.35 ω (sensitivity, 99.4%; specificity, 99.4%; AUC, and 100%) and the 0.50 Hz low-pass filter resulted in a turn detection threshold of 35.7 ω (sensitivity, 98.8%; specificity, 99.7%; and AUC, 100%). For the magnetometer data, using the 0.25 Hz low-pass filter resulted in a turn detection threshold of 1.98 μT' (sensitivity, 81.5%; specificity, 91.8%; and AUC, 92.5%).

Tables 6 and 7 show the percent of turns detected using the gyroscope and magnetometer data filtered at the different frequencies. Results from filters greater than 1.00 Hz were not presented due to no improvement in percent of turns detected compared to 1.00 Hz. For the gyroscope data, there were no significant main effects for walking and running speed or turn degree using a 0.25 Hz filter ($p > 0.05$). There were significant main effects for turn degree using a 0.50 Hz filter ($F(3, 251) = 31.786$; $p < 0.001$), walking and running speed using a 0.75 Hz filter ($F(3, 251) = 8.110$; $p < 0.001$)), and both walking and running speed ($F(3, 251) = 22.424$; $p < 0.001$) and turn degree ($F(3, 251) = 5.687$; $p = 0.001$) using a 1.00 Hz filter. There were no significant interactions between walking and running speed and turn degree for any filter ($p > 0.05$). In general, the number of 45° turns was underestimated using a 0.50 Hz filter. Using filters

of 0.75 Hz and higher, resulted in the number of turns being overestimated for all turn degree conditions.

For the magnetometer data, there was a significant interaction between walking and running speed and turn degree using the 0.25 Hz filter ($F(9, 251) = 8.206$; $p < 0.001$) and 0.50 Hz filter ($F(9, 251) = 6.142$; $p < 0.001$). There were significant main effects for walking and running speed using the 0.75 Hz ($F(3, 251) = 9.660$; $p < 0.001$) and 1.00 Hz ($F(3, 251) = 8.107$; $p < 0.001$) filters. There were significant main effects for turn degree using the 0.75 Hz ($F(3, 251) = 235.446$; $p < 0.001$) and 1.00 Hz ($F(3, 251) = 40.928$; $p < 0.001$) filters. In general, the number of 45° turns were underestimated using the 0.25 to 1.00 Hz filters. All filters overestimated the number of turns for the 90°, 135°, and 180° turn degree conditions, except the 0.75 Hz filter for the 5 and 6 mph 135° turning conditions.

Turn Degree

Gyroscope data low-pass filtered at 0.25 Hz were used for estimating turn degree due to the high sensitivity and specificity of the ROC-analysis and no significant main effects or interactions for number of turns detected across the walking and running turn conditions.

Table 8 shows the mean estimated turn degree error during walking and running. There were significant main effects for walking and running speed ($F(3, 251) = 5.949$; $p = 0.001$) and turn degree ($F(3, 251) = 2.907$; $p = 0.035$), however, there was no significant interaction between walking and running speed and turn degree ($F(9, 251) = 1.205$; $p = 0.292$). In general, turn degree was overestimated by approximately 3° for 45°, 90°, and 135° turns ($p < 0.05$) and underestimated by approximately 0.5° for 180° turns ($p > 0.05$).

Turning and Energy Expenditure

Table 9 shows the mean measured VO_2 for each walking and running turning condition. There were significant main effects for walking and running speed ($F(3, 315) = 882.518$; $p < 0.001$) and turn degree ($F(4, 315) = 40.956$; $p < 0.001$), but there was not a significant interaction between walking and running speed and turn degree ($p > 0.05$). VO_2 during the 135° turning condition were significantly greater than the 4 and 6 mph 0° conditions, 45° condition for all speeds, and 4 and 5 mph 90° conditions ($p < 0.05$). VO_2 of walking and running with 180° turns were significantly greater than 0°, 45°, and 90° conditions for all speeds ($p < 0.05$).

Table 10 shows the linear regression models for estimating VO_2. A strong association was observed between walking and running speed and VO_2 ($r = 0.915$). A weak association was observed between turn degree and VO_2 ($r = 0.187$). The addition of turn degree to the walking and running speed model increased the explained variance in VO_2 by 4.3% and reduced the standard error of the estimate by 0.5 ml/kg·min ($p < 0.001$).

Discussion

This study describes how the ActiGraph GT9X IMU can be used to detect the number of turns and estimate turn degree. The primary findings of this study are that; 1) a 0.25 Hz filter was best for turn detection, when using the gyroscope 2) a 0.75 Hz filter was best for turn detection, when using the magnetometer, and 3) turn degree can be estimated within approximately 2.2°, when using the gyroscope.

For the gyroscope, the 0.25 Hz and 0.75 Hz filters had the highest sensitivities, specificities, and AUCs. However, turn count error was lowest for the 0.25 Hz filter and it was the only gyroscope filter frequency that did not have significant main effects or interactions for detecting the number of turns. Previous studies have achieved turn detection sensitivities and

specificities greater than 76% using a low-pass filter (18) or device orientation estimates via Kalman filtering (55). El-Gohary et al. (18) low-pass filtered IMU data from the lower-back at 1.5 Hz to detect turns of 45°, 90°, 135°, and 180° during walking. Cross-validation against 3D-motion analysis resulted in a sensitivity and specificity of 90% and 76%, respectively. Pham et al. (55) processed raw IMU data from the lower-back with a Kalman filter to detect turns completed during ADL. Cross-validation against direct observation resulted in a sensitivity and specificity of 94% and 89%, respectively. The sensitivity (99.4%) and specificity (99.4%) achieved by filtering gyroscope data at 0.25 Hz in the current study was higher than Novak et al. (53) and Pham et al. (55). Differences in sensitivity and specificity between studies for turn detection may be attributed to device location or filtering methods. Since the lower lumbar is closer to the center of pelvic rotation, a device at the hip may experience greater angular velocities during walking and running. In theory, if using peaks in angular velocity to detect a turn as seen in El-Gohary et al. (18) and the current study, the greater angular velocities at the hip may explain the higher sensitivity and specificity of turn detection shown in the current study. Filtering frequency must also be considered as a factor for differences in turn detection between studies. As shown in Figure 3, lowering the frequency of the low-pass filter removes the noise in the signal, but also attenuates the angular velocity peaks. El-Gohary et al. (18) used a low-pass filtered at 1.5 Hz, which is higher than the filter frequency shown to be best for turn detection in the current study. Thus, improvements in turn detection may be achieved by changing the filter frequency, though the threshold for peak detection would also need to be changed accordingly.

For the magnetometer, the 0.25 Hz filter resulted in the best sensitivity, specificity, and AUC from the ROC-analysis. However, based on the cross-validation, the 0.75 Hz filtered

magnetometer data resulted in the lowest average turn-count error. Turns detected using the 0.25 Hz filter were underestimated by 9.7% for 45° turns and overestimated by 40.6% for all remaining speeds and turn degree conditions. Turns detected using the 0.75 Hz filter were underestimated by 65.5% for 45° turns at all speeds and 13.3% for 90° turns during running and overestimated by 22.5% for all remaining speeds and turn degree conditions. Except for 45° turns, percent of turns detected using the 0.75 Hz filter was better than 0.25 Hz. Unlike the gyroscope, there was no single filtering frequency that was best across all speeds and turn degrees.

Turn degree was estimated within 2.2° of the measured turn degree when using the gyroscope. Pham et al. (55) estimated turn degree within 0.06° using an IMU placed on the lower back, though they used a Kalman filter to estimate position. By using a Kalman filter, they utilize all components of the IMU to estimate position. In the current study, only the Y-axis of the gyroscope from the IMU was used to estimate turn degree. Thus, turn degree estimates can potentially be improved by utilizing additional axes from each sensor and/or different features of the signals.

Turn degree estimates using magnetometer data in this study could not be performed. In theory, any change in direction performed in an area without magnetic disturbances should cause a change in cardinal direction, which can be used to approximate the degree of the turn. For example, if indicated cardinal direction changed from north to south, it can be inferred that a 180° turn was performed. ActiGraph released a white paper (1) to convert simulated magnetometer data at the hip to cardinal direction (e.g. N, S), intercardinal direction (e.g. NE, SW), and secondary-intercardinal directions (e.g. NNE, SSW). Assuming that magnetometer data aligns with the scale, the identification of 22.5° turns or more should be possible from

changes in cardinal direction. In the current study, the magnetometer did not align with the scale (Table 2) as shown in Figure 8, which shows the magnetometer X-, Y-, and Z-axis data for 3 mph walking with 90° turns from one participant. The conversion scale utilizes the magnetometer X- and Z-axis to determine cardinal direction, though the data in Figure 8 would indicate that the participant was facing north for the duration of the trial and no turns were performed. This may have occurred due to magnetic interference as this has been reported as a confounding factor when using a magnetometer (60), though this was not measured or controlled for in the current study.

This study showed that compared to the walking and running 0° turn condition, VO_2 of walking and running was only significantly greater for the 135° and 180° turn conditions. This may have occurred due to the increased energy required to overcome the instantaneous moment of inertia associated with changing direction (58). With greater turn degrees, greater braking forces are applied in order to change direction while walking or running, followed by acceleration in the new directional heading (19, 75). Reilly et al. (59) showed that unorthodox modes of motion, such as running backwards or sideways, accelerating, decelerating, or changing direction, increases the metabolic loading. Directional changes of 45° and 90° during walking or running may not be sharp enough to induce significant increases in VO_2, though increases in VO_2 during 135° and 180° conditions as shown in the current study may be attributed to the propulsive and braking forces needed to complete turns.

Since turning can influence VO_2 at a given speed, this study examined how turn degree correlated with VO_2. Previous studies have shown that using gyroscope data, in addition to an accelerometer, increases the explained variability in VO_2 by 6.8% (50) and improves classification of activities by 4% (78), however, these studies used the gyroscope signal features

(e.g. mean, percentiles) within a given period of time as predictors to estimate VO_2. In the current study, the addition of turn degree was used as a predictor with speed, which only increased the explained variance in VO_2 by 4.3%. The correlation of turn degree with VO_2 ($r = 0.187$) was lower than the correlation between turn frequency and VO_2 reported by Hatamoto et al. (28) ($r = 0.991$), although they only examined 180° turns during walking and running. Since turn frequency was held constant across all trials, turn frequency may influence VO_2 more than turn degree.

This study has several strengths and limitations. Strengths of the study include, several walking and running speeds and turn degree conditions were used. Turn frequency, which has been shown to significantly impact VO_2, was the same across all trials to observe the impact of turn degree on walking and running VO_2. Limitations of the study include, participants were given the opportunity to choose the direction that they wanted to turn, and by chance all participants chose to complete their turns to the left. Turning during walking and running trials needed to be performed outdoors due to the space required, thus, a 3D-motion capture system could not be used to validate the estimated turn degree, as seen in other studies (18, 53). As a result, the actual degree of turns may have differed from the measured turn degree. Lastly, turns were examined only during walking and running activities.

In conclusion, this study shows the application of the ActiGraph GT9X gyroscope and magnetometer for detecting turns and estimating turn degree. Across all walking and running speeds and turn degrees examined, greater than 98% of turns were detected when using the gyroscope data filtered at 0.25 Hz. For the magnetometer, there was considerable over- and under-estimation of turns detected associated with all filter frequencies examined. On average, turn degree estimates were within 2.2° of the measured turn degree. In general, the VO_2 of

walking and running increased as the turn degree increased beyond 135°. Further examination of reliable methods to process magnetometer data into cardinal direction is needed. The application of the ActiGraph GT9X gyroscope must also be investigated for different turn frequencies, turns to the left and right, and turns performed during activities other than walking and running.

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APPENDIX

Table 1: Example of protocol performed by participants

Day 1	Day 2	Day 3
Change in postural orientation	Walking 3 mph	Walking 4 mph
• *Standing*	• *90°*	• *180°*
• *Sitting*	• *180°*	• *45°*
• *Laying supine*	• *45°*	• *90°*
• *Laying on the side*	• *135°*	• *135°*
Pivot Trials	Running 6 mph	Running 5 mph
• *45°*	• *135°*	• *45°*
• *90°*	• *45°*	• *90°*
• *135°*	• *180°*	• *135°*
• *180°*	• *90°*	• *180°*
Treadmill trials		
• *3 mph*		
• *4 mph*		
• *5 mph*		
• *6 mph*		

Table 2: ActiGraph scale to convert magnetometer data collected at the hip to cardinal direction

Cardinal Direction	X-axis Min (μT)	X-axis Max (μT)	Z-axis Min (μT)	Z-axis Max (μT)
N	22	∞	∞	-22
NNE	22	∞	-22	-16.71
NE	22	∞	-16.71	-11.43
ENE	22	∞	-11.43	-6.14
E	22	∞	-6.14	-0.86
ESE	22	∞	-0.86	4.43
SE	22	∞	4.43	9.71
SSE	22	∞	9.71	15
S	-	-	15	∞
SSW	∞	22	9.71	15
SW	∞	22	4.43	9.71
WSW	∞	22	-0.86	4.43
W	∞	22	-6.14	-0.86
WNW	∞	22	-11.43	-6.14
NW	∞	22	-16.71	-11.43
NNW	∞	22	-22	-16.71
N	∞	22	∞	-22

Table 3: Characteristics of sample population (mean ± SD)

Physical Characteristic	All Participants (N = 17)	Male (n = 11)	Female (n = 6)
Age (yr)	23.0 ± 2.9	23.1 ± 3.2	22.8 ± 2.4
Height (cm)	173.8 ± 9.8	178 ± 7.6	163.7 ± 6.0
Weight (kg)	71.0 ± 16.9	78.9 ± 15.6	56.5 ± 5.9
BMI (kg/m^2)	23.4 ± 3.1	24.7 ± 2.9	21.1 ± 2.0
Self-Reported PA Rating (0 to 7)	5.8 ± 1.6	5.45 ± 1.8	6.5 ± 0.8
Estimated VO_2max ($ml/kg \cdot min$)	48.2 ± 3.6	50.4 ± 2.1	44.3 ± 1.6

BMI, body mass index; PA, physical activity; VO_2, oxygen consumption.

Table 4: Receiver operator characteristic (ROC) thresholds for turn detection using gyroscope data filtered at 0.25, 0.50, 0.75, 1.00, 1.25, 1.50, and 2.00 Hz

Filter Frequency (Hz)	Threshold (ω)	Sensitivity	Specificity	AUC
0.25	12.3	0.994	0.994	1.000
0.50	35.7	0.988	0.997	1.000
0.75	41.5	0.988	0.991	0.996
1.00	62.8	0.959	0.991	0.990
1.25	79.4	0.909	0.979	0.981
1.50	89.1	0.891	0.965	0.971
1.75	95.0	0.877	0.941	0.960
2.00	95.6	0.885	0.885	0.948

AUC, area under the curve.

Table 5: Receiver operator characteristic (ROC) thresholds for turn detection using magnetometer data filtered at 0.25, 0.50, 0.75, 1.00, 1.25, 1.50, and 2.00 Hz

Filter Frequency (Hz)	Threshold (μT')	Sensitivity	Specificity	AUC
0.25	2.0	0.815	0.918	0.925
0.50	5.7	0.738	0.862	0.842
0.75	13.8	0.544	0.856	0.690
1.00	18.2	0.529	0.618	0.566
1.25	27.9	0.368	0.712	0.479
1.50	32.5	0.321	0.671	0.413
1.75	39.4	0.265	0.718	0.362
2.00	45.1	0.224	0.729	0.325

AUC, area under the curve.

Table 6: Percent of turns detected ((Estimated turns/expected turns)*100) ± SD during walking and running using gyroscope data

	Low-pass Filter Frequency (Hz)			
Condition	0.25	0.50	0.75	1.00
3 mph				
45°	100.6 ± 4.3	79.4 ± 23.6	114.7 ± 66.2	68.8 ± 84.0
90°	100.0 ± 0.0	105.9 ± 19.4	141.8 ± 55.3	131.2 ± 45.3
135°	100.0 ± 5.0	100.6 ± 5.6	148.2 ± 69.3	159.4 ± 65.7
180°	100.6 ± 4.3	100.6 ± 4.3	141.8 ± 61.5	178.8 ± 75.1
Overall	100.3 ± 3.9	96.6 ± 18.4	136.6 ± 63.2	134.6 ± 79.4
4 mph				
45°	100.0 ± 5.0	90.6 ± 19.2	158.2 ± 109.5	196.5 ± 254.8
90°	98.8 ± 3.3	105.3 ± 15.9	188.8 ± 134.2	247.1 ± 229.4
135°	100.0 ± 0.0	102.4 ± 4.4	194.1 ± 144.2	276.5 ± 243.6
180°	100.0 ± 3.5	99.4 ± 2.4	178.2 ± 163.6	278.2 ± 268.3
Overall	99.7 ± 3.4	99.4 ± 13.6	179.9 ± 136.8	249.6 ± 246.1
5 mph				
45°	100.0 ± 3.5	81.8 ± 17.8	103.5 ± 15.0	54.7 ± 36.6
90°	100.0 ± 0.0	101.8 ± 5.3	132.9 ± 38.5	147.1 ± 32.4
135°	102.4 ± 5.6	101.8 ± 5.3	121.2 ± 29.1	147.6 ± 41.9
180°	100.0 ± 3.5	99.4 ± 2.4	115.3 ± 24.0	161.2 ± 38.2
Overall	100.6 ± 3.8	96.2 ± 12.7	118.2 ± 29.4	127.6 ± 56.3
6 mph				
45°	100.0 ± 0.0	84.7 ± 21.3	105.3 ± 31.8	76.7 ± 112.2
90°	101.9 ± 8.3	103.8 ± 10.9	140.6 ± 45.4	167.5 ± 48.5
135°	102.5 ± 5.8	101.3 ± 3.4	128.8 ± 40.1	164.4 ± 53.0
180°	101.9 ± 6.6	96.9 ± 10.8	118.8 ± 34.2	166.3 ± 66.9
Overall	101.6 ± 6.0	96.8 ± 14.7	123.9 ± 39.6	144.8 ± 81.5
Main effect				
Speed	F(3,251) = 2.020; p = 0.112	F(3,251) = 0.888; p = 0.448	F(3,251) = 8.110; **p < 0.001**	F(3,251) = 11.977; **p < 0.001**
Turn Degree	F(3,251) = 0.858; p = 0.463	F(3,251) = 31.8; **p < 0.001**	F(3,251) = 1.934; p = 0.125	F(3,251) = 6.887; **p < 0.001**
Interaction				
Speed x Turn Degree	F(9,251) = 0.572; p = 0.819	F(9,251) = 0.702; p = 0.707	F(9,251) = 0.075; p = 1.000	F(9,251) = 0.110; p = 0.999

Table 7: Percent of turns detected ((Estimated turns/expected turns)*100) ± SD during walking and running using magnetometer data

	Low-pass Filter Frequency (Hz)			
Condition	0.25[c]	0.50	0.75	1.00
3 mph				
45°	92.9 ± 13.1	90.6 ± 23.0	38.8 ± 21.2	53.5 ± 42.3
90°	106.5 ± 8.6	130.0 ± 20.0	111.2 ± 22.9	116.5 ± 42.1
135°	132.4 ± 19.5	157.1 ± 25.9	135.3 ± 45.8	167.1 ± 99.8
180°	130.0 ± 21.2	124.7 ± 22.9	113.5 ± 14.5	115.3 ± 15.5
Overall	115.4 ± 23.1	125.6 ± 32.8	99.7 ± 46.1	113.1 ± 70.2
4 mph				
45°	88.8 ± 9.3	92.4 ± 14.8	52.9 ± 31.2	98.2 ± 63.4
90°	108.8 ± 11.1	134.7 ± 19.7	111.2 ± 26.0	175.9 ± 88.3
135°	144.7 ± 18.7	168.8 ± 25.7	144.7 ± 29.2	192.9 ± 71.8
180°	138.8 ± 18.0	159.4 ± 31.5	121.2 ± 11.1	128.2 ± 17.8
Overall	120.3 ± 27.1	138.8 ± 37.8	107.5 ± 42.2	148.8 ± 74.6
5 mph				
45°	92.4 ± 12.0	85.9 ± 11.8	21.2 ± 14.1	51.2 ± 62.3
90°	115.9 ± 15.8	125.9 ± 28.3	85.3 ± 21.2	99.4 ± 38.2
135°	164.1 ± 20.3	174.7 ± 28.1	125.9 ± 23.5	145.3 ± 64.5
180°	159.4 ± 24.6	171.8 ± 33.8	119.4 ± 16.8	140.0 ± 44.0
Overall	132.9 ± 35.4	139.6 ± 45.2	87.9 ± 45.9	109.0 ± 64.7
6 mph				
45°	86.7 ± 11.8	86.7 ± 16.8	24.0 ± 12.4	53.3 ± 38.9
90°	122.5 ± 21.1	123.8 ± 18.2	88.1 ± 23.7	106.3 ± 29.4
135°	188.1 ± 24.8	190.6 ± 37.0	138.8 ± 14.5	166.9 ± 34.4
180°	179.4 ± 19.5	195.6 ± 34.1	112.5 ± 19.8	120.6 ± 28.6
Overall	145.1 ± 6.0	150.2 ± 53.5	91.9 ± 46.0	112.7 ± 51.7
Main Effect				
Speed	F(3,251) = 35.447; **p < 0.001**	F(3,251) = 9.516; **p <0.001**	F(3,251) = 9.660; **p <0.001**	F(3,251)=8.107; **p < 0.001**
Turn Degree	F(3,251)=220.046; **p < 0.001**	F(3,251)=147.468; **p < 0.001**	F(3,251)=235.446; **p < 0.001**	F(3,251) = 40.928; **p <0.001**
Interaction				
Speed x Turn Degree	F(9,251) = 8.206; **p < 0.001**	F(9,251) = 6.142; **p <0.001**	F(9,251) = 1.842; p = 0.061	F(9,251) = 1.553; p = 0.130

Table 8: Turn degree error (°) of turns detected (mean ± SD) using 0.25 Hz low-pass filtered gyroscope data

Condition	Turn Degree Error (°)	95% CI for Mean	
		Lower Bound	Upper Bound
3 mph			
45°	3.2 ± 2.2	-0.9	7.2
90°	5.0 ± 3.4*	0.9	9.0
135°	6.7 ± 5.2*	2.6	10.7
180°	4.9 ± 8.0*	0.8	9.0
Overall	4.9 ± 5.2*	2.9	7.0
4 mph			
45°	2.5 ± 2.9	-1.6	6.6
90°	4.0 ± 4.0	-0.1	8.1
135°	3.8 ± 5.5	-0.3	7.9
180°	2.5 ± 7.8	-1.6	6.5
Overall	3.2 ± 5.3*	1.2	5.2
5 mph			
45°	2.1 ± 3.6	-2.0	6.2
90°	2.5 ± 4.8	-1.6	6.6
135°	2.1 ± 7.3	-1.9	6.2
180°	-0.5 ± 10.8	-4.6	3.6
Overall	1.6 ± 7.1	-0.5	3.6
6 mph			
45°	1.2 ± 3.7	-3.1	5.6
90°	1.6 ± 6.3	-2.6	5.8
135°	1.08 ± 8.8	-3.1	5.3
180°	-8.5 ± 25.2*	-12.7	-4.3
Overall	-1.2 ± 14.3	-3.3	1.0

CI, confidence interval; LB, lower bound; UB, upper bound; * significantly different from measured turn degree; $p < 0.05$.

Table 9: Mean VO_2 ± SD (mL/kg·min) for walking and running during 0°, 45°, 90°, 135°, 180° turn conditions

	Turn Condition				
Speed (mph)	**0°**	**45°**	**90°**	**135°**	**180°**
3.0	15.4 ± 1.2	14.1 ± 1.4	15.3 ± 1.7	17.0 ± 2.4[b]	18.3 ± 2.3[a,b,c]
4.0	21.8 ± 2.3	21.0 ± 2.2	22.7 ± 2.5	25.9 ± 2.9[a,b,c]	27.7 ± 3.3[a,b,c]
5.0	31.9 ± 3.0	29.6 ± 2.5	31.1 ± 3.0	34.0 ± 3.2[b,c]	35.1 ± 3.7[a,b,c]
6.0	35.9 ± 3.5	35.1 ± 3.7	36.8 ± 3.6	39.5 ± 3.5[a,b]	41.2 ± 4.3[a,b,c]

VO_2, oxygen consumption; [a] significantly different from 0°; [b] significantly different from 45°; [c] significantly different from 90°; $p < 0.05$.

Table 10: Linear regression model summaries to estimate VO_2 (ml/kg·min)

		β-coefficient			
Model	**Y-Intercept**	**Speed**	**Turn Degree**	**R^2**	**SEE**
Speed	-5.71	7.38	-	0.838	3.62
Turn Degree	23.72	-	0.03	0.035	8.92
Speed, Turn Degree	-10.57	7.51	0.04	0.881	3.14

SEE, standard error of the estimate.

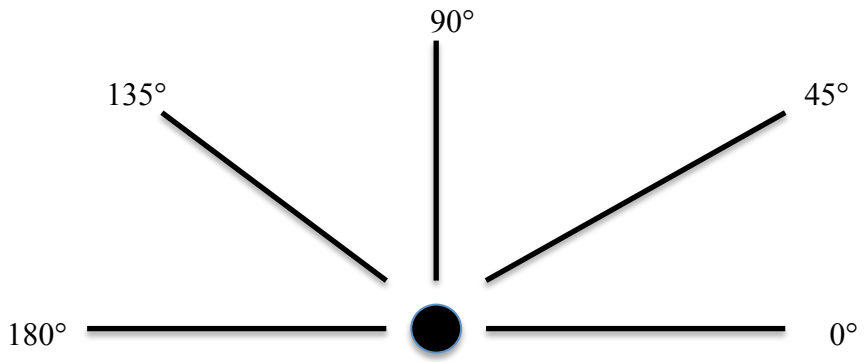
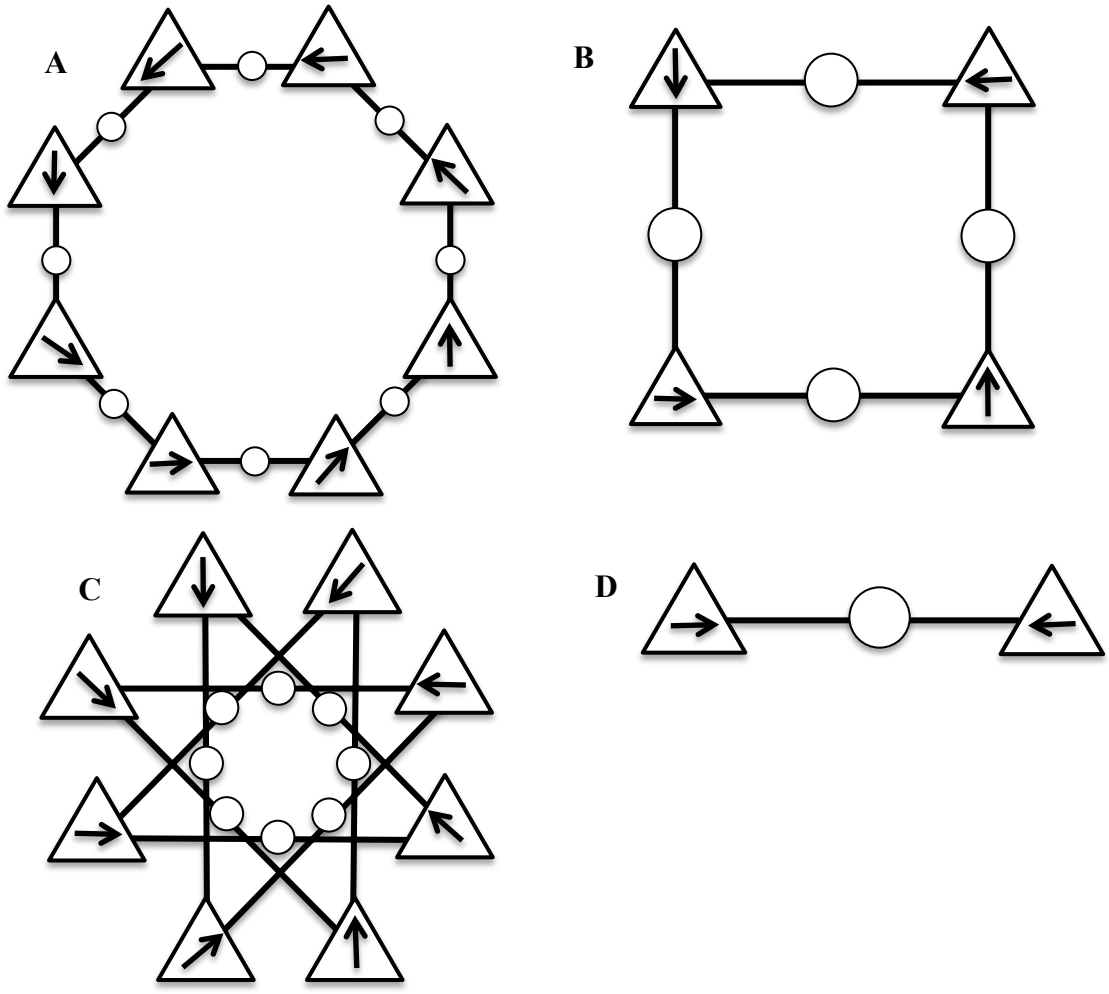


Figure 1: Pivot trial layout



Δ = turning points, o = midpoints

Figure 2: Layout of 45° (A), 90° (B), 135° (C) and 180° (D) turning during over-ground walking and running trials

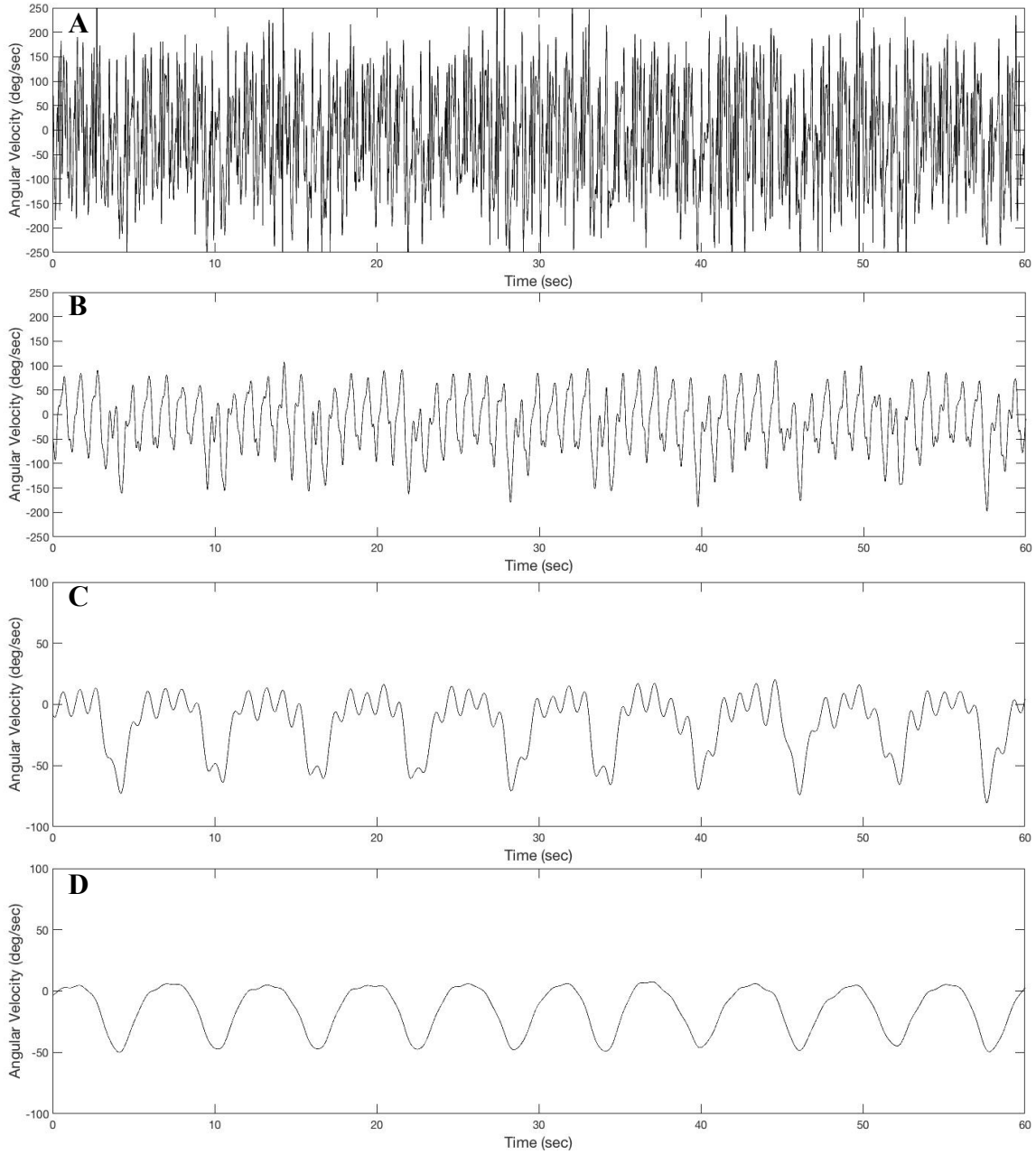


Figure 3: Sample gyroscope Y-axis data for 90° turns when walking at 3 mph for (A) unfiltered, (B) low-pass filtered at 2.00 Hz, (C) low-pass filtered at 0.50 Hz, and (D) low-pass filtered at 0.25 Hz

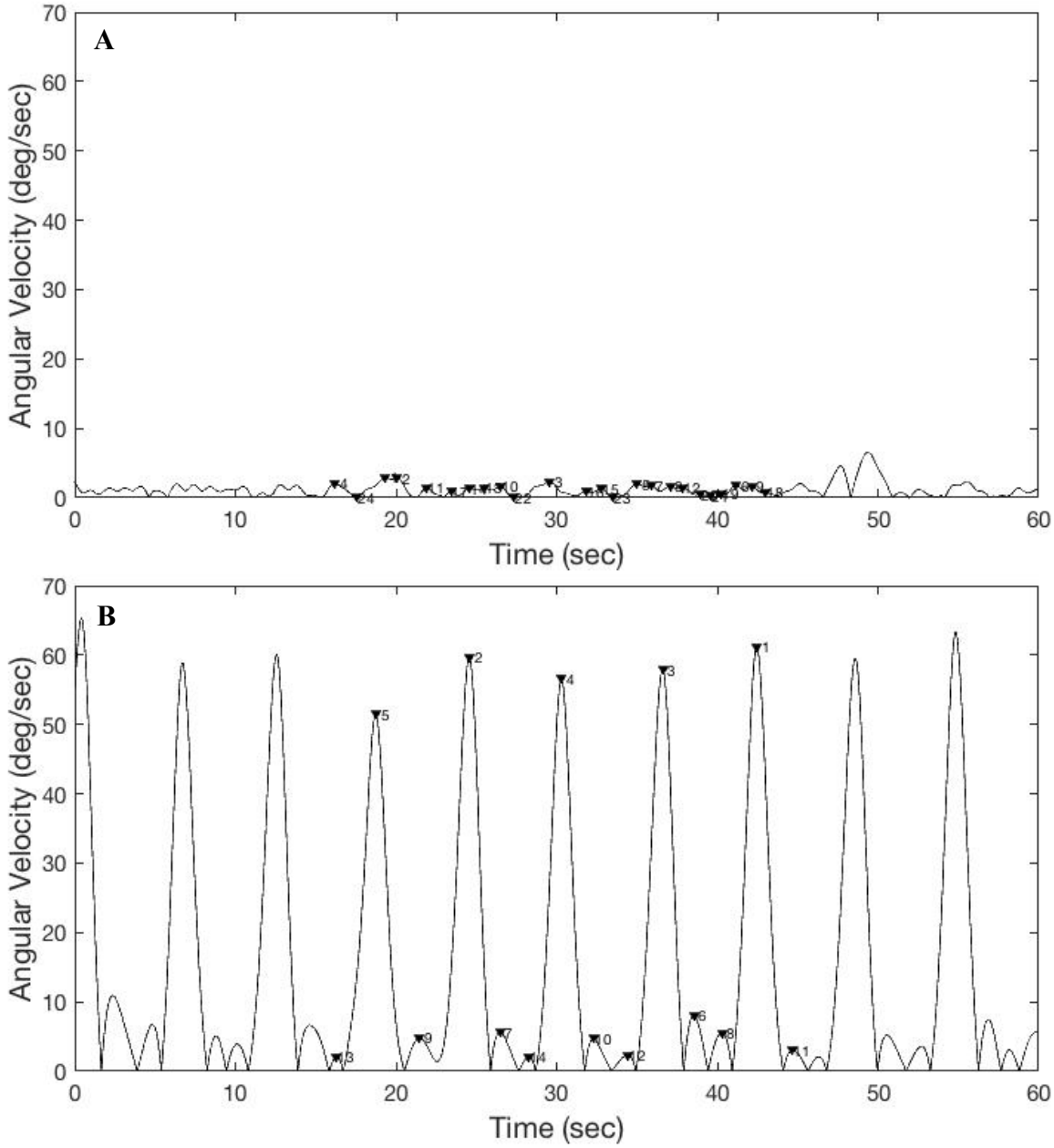


Figure 4: Sample full-wave rectified gyroscope Y-axis data filtered at 0.25 Hz for (A) 3 mph treadmill walking and (B) 90° pivot trial for peak detection and selection

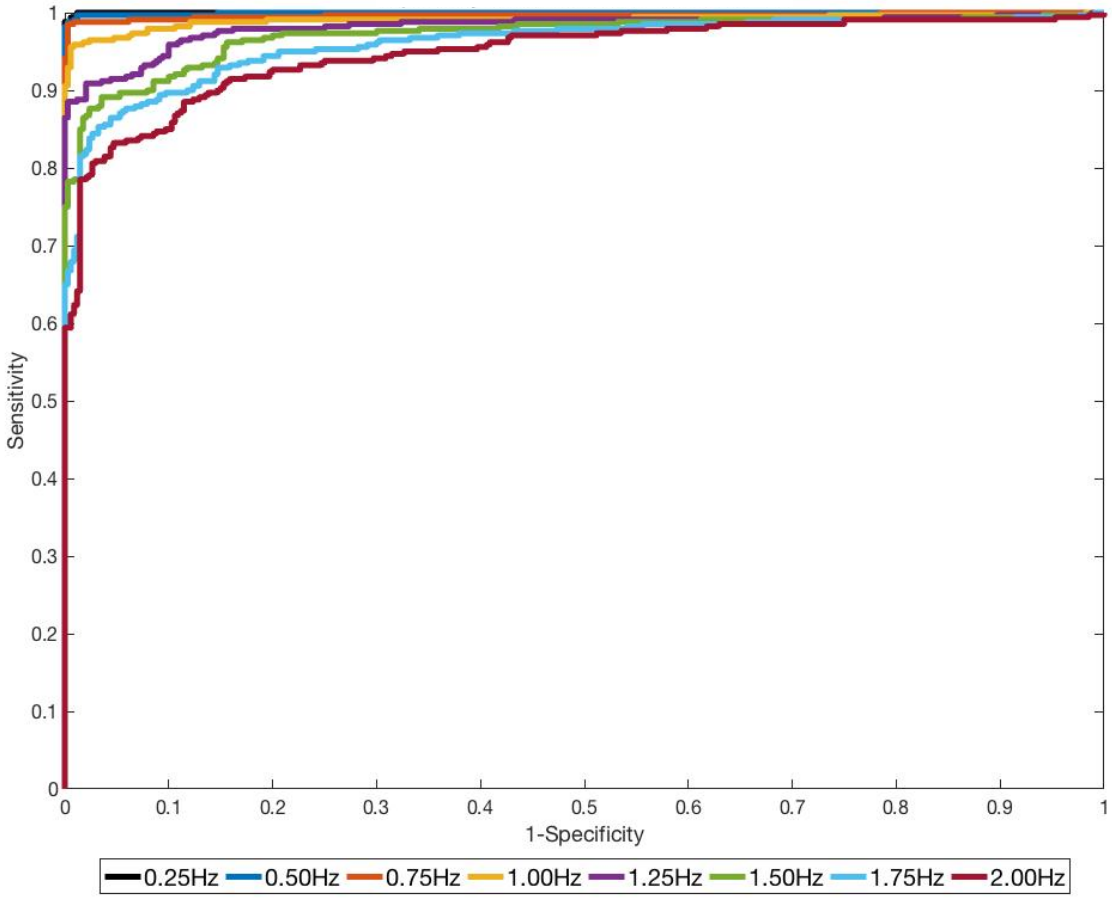


Figure 5: Receiver operator characteristic (ROC) curves for turn detection using the gyroscope filtered at 0.25, 0.50, 0.75, 1.00, 1.25, 1.50, and 2.00 Hz

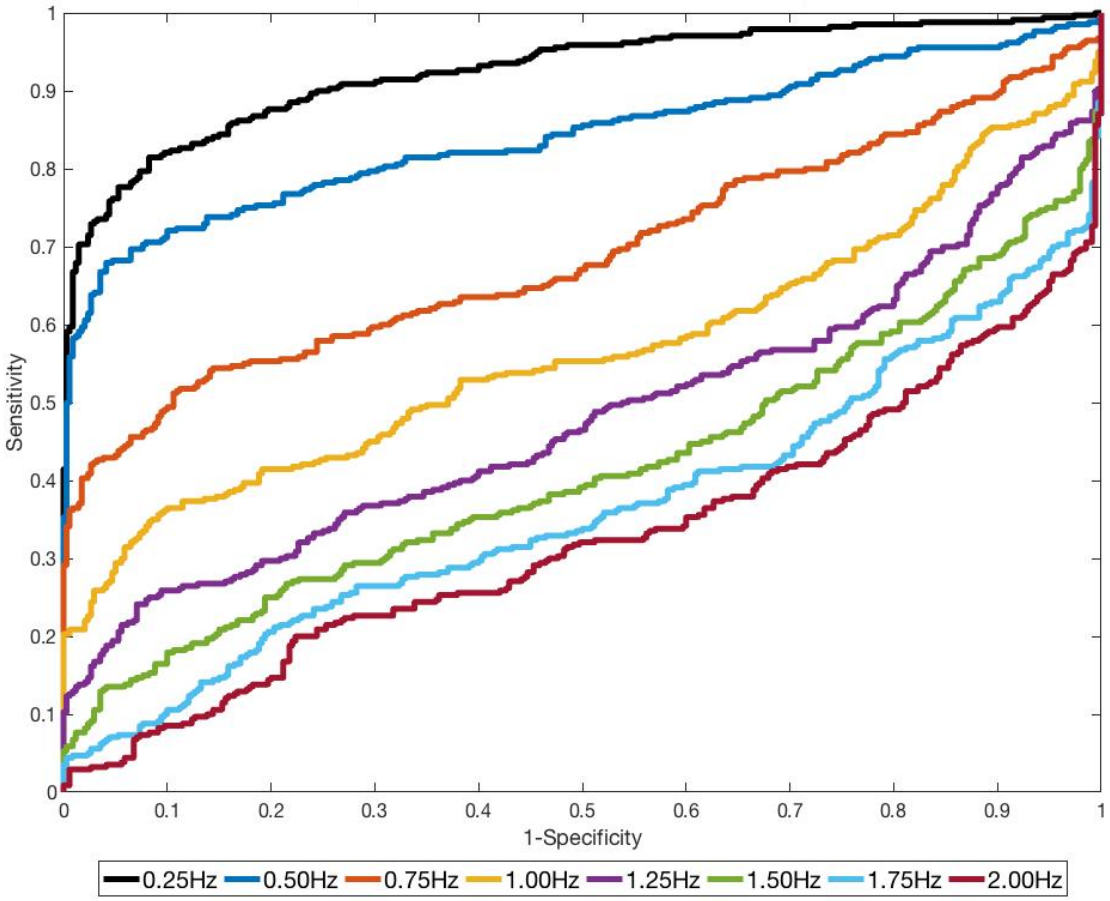


Figure 6: Receiver operator characteristic (ROC) curves for turn detection using the magnetometer filtered at 0.25, 0.50, 0.75, 1.00, 1.25, 1.50, and 2.00 Hz

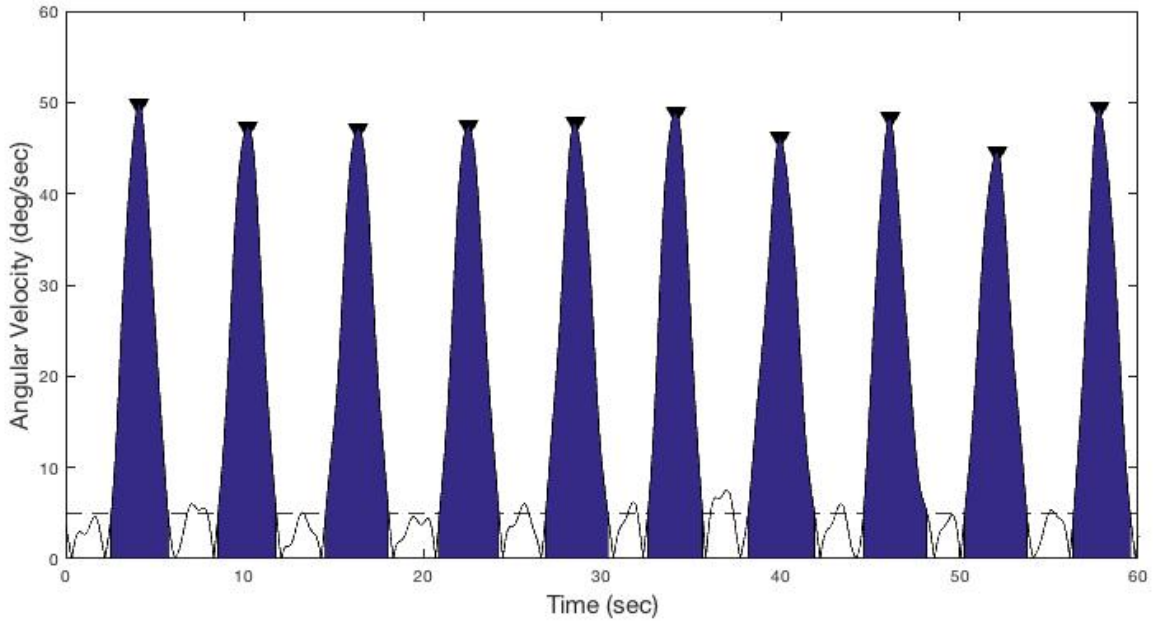


Figure 7: Sample gyroscope Y-axis data for 3 mph walking with 90° turns to estimate the degree of detected turns

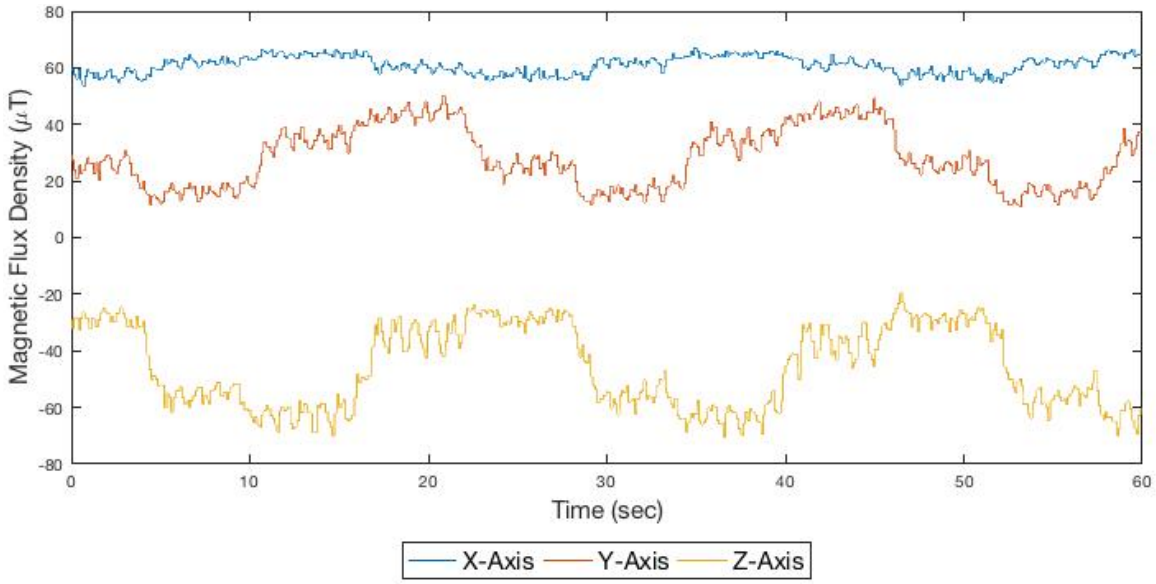


Figure 8: Sample magnetometer Y-axis data for 3 mph walking with 90° turns

Informed Consent Statement

Title of Research**:** Application of the ActiGraph GT9X IMU in the Assessment of Turning While Walking and Running

Principal Investigator: Robert Marcotte, B.S.
Advisor: Scott E. Crouter, Ph.D.

Location: Applied Physiology Laboratory, 1914 Andy Holt Ave., University of Tennessee, Knoxville, TN 37996

INTRODUCTION
You are invited to participate in a research study that will require 3 separate testing days lasting approximately 1 hr on each day. The first purpose of this study is to examine the use of motion sensors, positioned at various body locations (e.g. hip, ankle, and wrist), in evaluating changes in direction while walking and running. The second purpose of this study is to observe changes in energy expenditure across different turning degrees and locomotion speeds.

INFORMATION ABOUT PARTICIPANTS' INVOLVEMENT IN THE STUDY
1. You will receive this informed consent form and be given a chance to ask questions. If you choose to participate, you will be asked to fill out a Physical Activity Readiness Questionnaire (PAR-Q) contains 7 questions about your health status to ensure it is safe for you to participate in the study. If you answer "Yes" to any question on the PAR-Q, you will be excluded from participation in the study.
2. You will have your height and weight measured and you will be asked a series of questions regarding age and perceived current physical activity level. These will be used to estimate your VO_2max (a measure of your maximal fitness level). If your predicted VO_2max is less than 40 ml/kg/min, you will be excluded from participation in the study.
3. During all activities, you will be asked to wear a facemask that will be attached to a portable unit that is worn on your upper body and weighs approximately 4 pounds. The facemask will surround your nose and mouth area allowing us to measure your energy expenditure while performing the activities.
4. You will be wearing an activity monitor on the left and right wrists, hips, and ankles during all testing.
5. On day 1, the activities will be performed in the Health, Physical Education, and Recreation building on campus at the University of Tennessee in Room 310. You will be asked to complete 8 activities for 1 minute each (standing, sitting, laying on your back, laying on your side, and pivoting at 45, 90, 135, and 180 degrees). You will also be asked to walk (3 and 4 mph) and run (5 and 6 mph) on a treadmill for 6 minutes at each speed. 1-3 minute recovery will be given between each activity.
6. On days 2 and 3, the activities will be performed at Fulton Bottom Rugby Fields on The University of Tennessee-Knoxville campus. You will be randomly assigned one walking (3 mph or 4 mph) and one running speed (5 mph or 6 mph) for Day 2 and the other speeds will be performed on Day 3. During the walking/running trials, you will perform a specific degree of turn every six seconds. All locomotion trials will be performed for 6 minutes each with 1-3 minutes of recovery between each activity.
   Day 2 & 3 (Participation Time Per Day: 48 minutes of activity + rest)
   - Walking 3 or 4 mph
     - 45°
     - 90°
     - 135°
     - 180°
   - Running 5 or 6 mph
     - 45°
     - 90°
     - 135°
     - 180°
7. You may stop the testing at any time if you experience feelings of fatigue or any other discomfort. The researcher also may stop the test at any time because of signs of fatigue, symptoms you may be experiencing, equipment malfunction, or not completing the task correctly.

Total time commitment for this study will be 3 hours (~1 hour/day of data collection).

Initials _____

IRB NUMBER: UTK IRB-17-03474-XP
IRB APPROVAL DATE: 03/20/2017
IRB EXPIRATION DATE: 12/26/2018

RISKS
Possible loss of confidentiality is a risk that may occur related to participation in research. The risks associated with exercising are slight in a healthy population. Risks associated with walking and running are minimal and considered equivalent to what you could experience in daily living. There is also a slight risk that you could suffer an accidental injury with the incorporation of turns during locomotion, To minimize the risk of exercise, you will be screened using a Physical Activity Readiness Questionnaire. In addition, the investigators are certified in Cardiopulmonary Resuscitation (CPR). You may also experience mild skin irritation while wearing the face mask. If discomfort or irritation should arise while wearing the facemask or devices, they will be adjusted for comfort or removed. Should symptoms of fatigue arise from participation, investigators will cease testing and you will be allowed additional rest time to recover or you may stop participation in testing procedures. If injury is to occur, first aid will be performed accordingly.

BENEFITS
There are no direct benefits to you from this study. Results from this study may help improve physical activity assessment techniques specific to walking and running.

CONFIDENTIALITY
Information and records included in this study will be kept confidential in the Health, Physical Education and Recreation Building Room 307. Data will be stored in a secure location and will only be made available to the people conducting the study, unless you specifically give permission in writing to do otherwise. The results of the study will be published, but no reference will be made in oral or written reports that could link you to the study.

COMPENSATION
There will be no compensation for participating in this research study.

EMERGENCY MEDICAL TREATMENT
The University of Tennessee does not “automatically” reimburse subjects for medical claims or other compensation. If physical injury is suffered in the course of research, or for more information, please notify the investigator in charge, Robert Marcotte, at (865) 974-5091.

CONTACT INFORMATION
Questions about the study (or if you experience adverse effects as a result of participating in this study) should be addressed to Robert Marcotte, 314 HPER Building, The University of Tennessee, Knoxville, TN 37996, (865) 974-5091, rmarcott@vols.utk.edu, or his advisor, Dr. Scott Crouter, (865-974-1272, scrouter@utk.edu). If you have questions concerning your rights as a participant, contact the Office of Research Compliance Officer at (865) 974-7697.

PARTICIPATION
Your participation in the study is voluntary; you may decline to participate without penalty. If you decide to participate, you may withdraw from the study at any time without penalty and without loss of benefits to which you are otherwise entitled. You may be excluded or withdrawn from the study as a result of no longer meeting the aforementioned eligibility criteria or maintaining compliance with study procedures. Should this occur or if you withdraw from the study before data collection is completed, your data will be returned to you or destroyed.

STATEMENT OF CONSENT
I have read the above information. I have received a copy of this form. I agree to participate in this study.

_____ _____
Participant Signature Date

_____ _____
Researcher Signature Date

IRB NUMBER: UTK IRB-17-03474-XP
IRB APPROVAL DATE: 03/20/2017
IRB EXPIRATION DATE: 12/26/2018

Physical Activity Readiness Questionnaire (PARQ)

	Questions	Yes	No
1	Has your doctor ever said that you have a heart condition and that you should only perform physical activity recommended by a doctor?		
2	Do you feel pain in your chest when you perform physical activity?		
3	In the past month, have you had chest pain when you were not performing any physical activity?		
4	Do you lose your balance because of dizziness or do you ever lose consciousness?		
5	Do you have a bone or joint problem that could be made worse by a change in your physical activity?		
6	Is your doctor currently prescribing any medication for your blood pressure or for a heart condition?		
7	Do you know of any other reason why you should not engage in physical activity?		

If you have answered "Yes" to one or more of the above questions, consult your physician before engaging in physical activity. Tell your physician which questions you answered "Yes" to. After a medical evaluation, seek advice from your physician on what type of activity is suitable for your current condition.

IRB NUMBER: UTK IRB-17-03474-XP
IRB APPROVAL DATE: 01/26/2017

PHYSICAL FITNESS ACTIVITY 3.5

Estimation of $\dot{V}O_{2max}$ Using an Equation

Low levels of cardiorespiratory fitness have been linked to most of the leading causes of death, including heart disease, stroke, cancer, and diabetes. Direct measurement of cardiorespiratory fitness or $\dot{V}O_{2max}$ is expensive and requires trained technicians and medical supervision. There has been much interest in developing simple methods of estimating $\dot{V}O_{2max}$, especially for large groups of people. One method that is gaining widespread acceptance is the use of an estimating equation that factors in several personal characteristics including age, gender, height, weight, and physical activity habits.

Use the equation below to estimate your $\dot{V}O_{2max}$. You will need a calculator. Calculate your body mass index (BMI) from Figure 4.11. It should be emphasized that this equation provides a "ballpark" estimate of your $\dot{V}O_{2max}$, and that other methods, especially running and walking tests, are preferred. Once you estimate your $\dot{V}O_{2max}$, use Table 24 in Appendix A to obtain your classification.

Equation for Estimating $\dot{V}O_{2max}$

$\dot{V}O_{2max}$ ml · kg^{-1} · min^{-1} = _____ _____
Classification (Table 24, Appendix A)

56.363 − (_____ × 0.381)
age

− (_____ × 0.754)
body mass index

+ (_____ × 1.921)
physical activity rating, 0 to 7*

+ 10.987 (if you are a male) or 0 (if you are a female)

Example: Calculate $\dot{V}O_{2max}$ in ml · kg^{-1} · min^{-1} for a 20-year-old female college student who is 5 ft, 5 in. tall (65 in.), weighs 130 lb, and swims laps 45 minutes each week.

$\dot{V}O_{2max}$ ml · kg^{-1} · min^{-1} = 42.0 Average
Classification (Table 24, Appendix A)

56.363 − (20 × 0.381)
age

− (21.7 × 0.754)
body mass index

+ (5 × 1.921)
physical activity rating, 0 to 7*

+ 0 (female)

*Pick a physical activity rating that best fits your typical habits:

I. Does not participate regularly in programmed recreation sport or physical activity.
   0 points: Avoids walking or exertion (e.g., always uses elevator, drives whenever possible instead of walking)
   1 point: Walks for pleasure, routinely uses stairs, occasionally exercises sufficiently to cause heavy breathing or perspiration.

II. Participates regularly in recreation or work requiring modest physical activity, such as golf, horseback riding, calisthenics, gymnastics, table tennis, bowling, weight lifting, or yard work.
   2 points: 10 to 60 minutes per week.
   3 points: Over 1 hour per week.

III. Participates regularly in heavy physical exercise (such as running or jogging, swimming, cycling, rowing, skipping rope, running in place) or engages in vigorous aerobic-type activity (such as tennis, basketball, or handball).
   4 points: Runs less than 1 mi per week or spends less than 30 minutes per week in comparable physical activity.
   5 points: Runs 1 to 5 mi per week or spends 30 to 60 minutes per week in comparable physical activity.
   6 points: Runs 5 to 10 mi per week or spends 1 to 3 hours per week in comparable physical activity.
   7 points: Runs over 10 mi per week or spends over 3 hours per week in comparable physical activity.

VITA

Robert Thomas Marcotte was born on July 27, 1993 to Norman R. Marcotte and Mimi K. Marcotte. Robert completed his Bachelor's of Science in Human Nutrition, Foods, and Exercise at Virginia Tech in May of 2015. In Fall of 2015, he enrolled in the Kinesiology Master's of Science program with a concentration in Exercise Physiology at The University of Tennessee-Knoxville. Robert graduated from the Master's program in the August of 2017 and enrolled at The University of Massachusetts-Amherst as a doctoral candidate in Kinesiology with a concentration in Physical Activity and Health. Robert intends to begin a career teaching at the University level upon completion of his doctoral studies.