35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Using a foot mounted accelerometer to detect changes in gait patterns

Matthew R. Patterson, *Student Member IEEE* and Brian Caulfield, *Member, IEEE*

Abstract— **The purpose of this study is to investigate how data from a foot mounted accelerometer can be used to detect motor pattern healthy subjects performed walking trails under two different conditions; normal and stiff ankle walking. Lower body kinematic data were collected as well as accelerometer data from both feet. An algorithm is presented which quantifies relevant swing phase characteristics from the foot accelerometer. Peak total acceleration during initial swing was significantly higher in the stiff ankle condition (M = 33.10, SD = 5.12) than in the normal walking condition (M = 29.47, SD = 5.75; t(7) = 4.32, p = .003, two-tailed). There was a large effect size (eta squared = 0.853). Time between peak acceleration during initial swing to foot strike was significantly shorter in the stiff ankle condition (M = 0.42, SD = 0.02) than in the normal condition (M = 0.44, SD = 0.03; t(7) = -2.54, p = .039, two- tailed). There was a large effect size (eta squared = 0.693). Simple to process metrics from tri-axial accelerometer data on the foot show potential to detect changes in ankle kinematic patterns.**

I. Introduction

Traditional gait analysis tools are expensive and take a significant amount of time to obtain data from [10]. These factors severely limit how often gait analyses can be performed on a patient and also limit the number of patients gait analysis can be performed on. The complexity and cost associated with traditional gait analysis techniques it is important for research to address issues concerning the use of wearable sensor technology which may allow gait analysis to be accessible to more patients in easier to use and deployable applications outside the laboratory [7].

A significant body of work in the ambulatory monitoring field has gone into using inertial measurement units to determine kinematic data during various movements [11, 12]. This approach provides useful data in an easier to use set-up than traditional measurement techniques. However, the fact that sensors are required on each body segment limits such an approach from being applied to deployable, every-day monitoring applications. Long-term patient monitoring has traditionally obtained metrics such as activity recognition, calorie counting or step-counting. While these metrics are very useful for many clinicians, there is an opportunity to obtain more detailed quality of movement data from the sensors that are used to obtain these gross metrics.

Using shoe embedded sensors is a promising opportunity for ambulatory gait monitoring, since it does not require a user to apply any extra sensors. Foot mounted sensors have been used most commonly to assess spatio-temporal parameters of gait [18]. Accelerometers at the foot have been used to detect foot strike (FS) [6]. The addition of a gyroscope allows for toe-off (TO) identification as well as measurement of step length [5, 8, 9]. Spatio-temporal parameters are useful for identifying important phases of the gait cycle, for calorie estimation and for identifying large changes in movement patterns. However, kinematic changes in gait are not always associated with changes in step time and step length. Early disease or injury development could potentially be detected by identifying changes in lower body kinematics that are not necessarily associated with spatio-temporal changes in gait.

Previous work has shown the potential for shoe mounted accelerometers to predict lower body kinematic patterns during gait in a long-term monitoring scenario [13]. This approach only worked well when a complex calibration was performed on each patient. Perhaps, replicating traditional measurement tools is not necessary. Perhaps, the inertial data from the foot on its own could be used to determine if an abnormal gait pattern exists.

Capturing gait metrics with inexpensive sensors in an unobtrusive manner, while people go about their daily lives would allow for more patients to have their gait analyzed on a regular basis [1]. This may allow more people to live healthier lives and decrease health-care costs by allowing for earlier intervention in disease and injury development [21]. The aim of this investigation is to determine if data from a foot mounted accelerometer can be used to identify change in a person's gait patterns.

II. Methods

Eight participants were recruited for the study; six female and two male. Ethical approval was granted by the Universities ethical review board and each subject signed an informed consent form. The participants average age was 27.4 years (+/- 2.67 years), their average weight was 59.1 kgs (+/- 12.4 kgs) and their average height was 1.68m (+/- 0.11m).

Each subject performed ten 15m walking trials in a biomechanics laboratory under two conditions; normal walking and a simulated stiff ankle gait. Stiff ankle gait was simulated by use of a lace up ankle brace which restricted ankle plantar-flexion. Both conditions were done at the same

*This work was supported by Science Foundation Ireland under grant 07/CE/I1147.

M. Patterson is with the CLARITY Centre for Sensor Web Technologies and the School of Public Health, Physiotherapy and Population Science, University College Dublin, Belfield, Dublin 4, Ireland. Phone +353 1 7166500, email: matt.patterson@ucd.ie.

B. Caulfield is with the CLARITY Centre for Sensor Web Technologies, the TRIL Centre, and the School of Public Health, Physiotherapy and Population Science, University College Dublin, Belfield, Dublin 4, Ireland (email: b.caulfield@ucd.ie).

978-1-4577-0216-7/13/$26.00 ©2013 IEEE

walking speed. Walking speed was determined at the end of each trial by finding stride distance and stride time for the right heel marker and dividing them together. An average walking speed was determined from the normal walking trials and stiff ankle trials were only included if they were within 0.20 m/s of the normal walking average. The stiff ankle condition was included to attempt to replicate diseases that result in limited ankle range of motion; such as Parkinson's disease, stroke, diabetes mellitus and cerebral palsy [14, 15]. Ankle sprains and injuries can also result in abnormal plantar-flexion activity during walking. Subjects wore their normal, everyday shoes during the walking trials.

A CODA motion capture system (Charnwood Dynamics, Leicestershire, UK) was used to collect kinematic data. Markers were placed on the participants right and left sides at the following locations, PSIS, ASIS, greater trochanter, femoral condyle, fibular head, lateral malleolus, heel and 5th metatarsal. An IMU (Xsens MTx, Enschede, Netherlands) was placed on the dorsal aspect of each subjects shoe above the shoe laces, held in place with athletic tape. The sensor was placed on the dorsum on each foot so that the distal aspect of the sensor lined up with a perpendicular line coming from the 5th metatarsal (Fig 1).

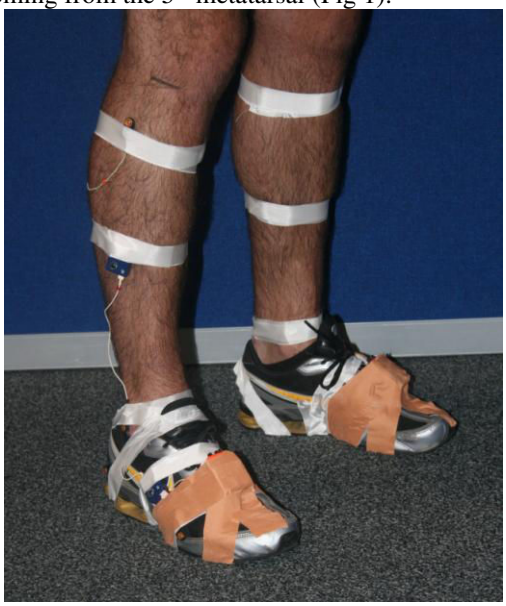

Figure 1. Inertial sensor placement on the dorsum of the foot. The local x and y acceleration were used to find FS as well as to quantify aspects of the swing phase during gait.

A. *Accelerometer processing*

Accelerometer data was analyzed using MATLAB 2009b (Mathworks, Massachusetts, USA). Gyroscope and angle data were not used because the purpose of this study was to see if accelerometer data alone could be used to determine changes in gait patterns. Total acceleration (TA) was calculated from x, y and z acceleration signals by using equation 1.

$$Total\ acceleration\ (TA) = sqrt\ (Ax^2+Ay^2+Az^2) \qquad (1)$$

The 3-axis data were transformed due to the fact that looking at specific axes is very sensitive to how the sensor is mounted on the shoe. Very small changes in mounting location could be erroneously flagged as a change in movement if the data were to be looked at on each axis individually. This is a trade off and it has been chosen to pick usability at the expense of accuracy. TA cannot show what is happening in which axis, but by using TA it means that any user can mount the sensor on their shoe properly and will be able to generate useful results. This is important for the case where a user is mounting a sensor on their shoe or a manufacturer is creating the shoe with a 3-axis accelerometer built in.

An algorithm was created to quantify aspects of the acceleration signal from each walking trial post test. First, the fundamental frequency of TA was determined and then TA was band pass filtered between 0.3 Hz to the fundamental frequency. On the sinusoidal resultant curve, positive going zero crossings were used to estimate where initial swings were and negative going zero crossings were used to estimate where FS occurred. Initial swing peaks were found in a range around the positive going zero crossing point and FS was found according to a previously published method [6].

Two variables were calculated from the accelerometer data. Peak TA during initial swing (PTAIS) and the time between PTAIS to FS (TTAFS). Figure 1 shows a typical TA curve during a gait cycle and where these features occur. PTAIS is of interest because it shows how quickly the foot is being moved just after TO. Abnormal movement patterns around TO are likely to result in different acceleration patterns during initial swing and PTAIS may be able to pick these up. TTAFS is a timing variable which likely has a scalar relationship to swing time, but requires less processing and sensors to find since it does not include TO.

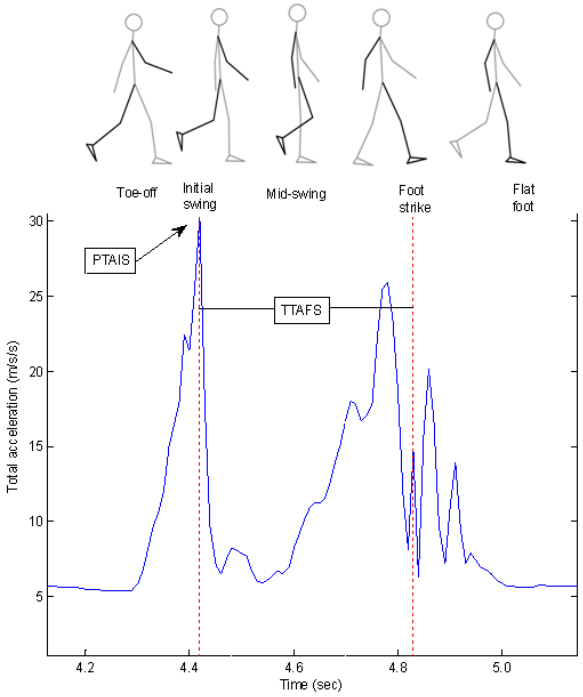

Figure 2. TA data from the right foot for a typical swing cycle and the quantified accelerometer variables. The dark limbs on the stick figure represent the right arm and leg.

B. Statistics

The accelerometer variables were averaged over each of the five trials for each condition for each subject. A two-tailed, paired samples t-test was used to test the null hypothesis that the accelerometer variables could not detect the change in gait between the constrained gait conditions and their speed matched controlled conditions.

A two-tailed, paired samples t-test was also used to investigate differences in walking speed and ankle kinematics to see if there was a significant difference in these factors between the conditions. Associated effect sizes (eta squared) were calculated and quantified according to Field as 0.10 = small effect size, .030 = medium effect size and 0.50 = large effect size [3]. The level of significance was set at $p < 0.05$.

III. Results

There was not a statistically significant difference in walking speed between the normal (M = 1.422, SD = .141) and stiff ankle walking condition (M = 1.366, SD = .195), $t(7) = 1.55$, $p = .165$ (Table 1).

Peak ankle plantar-flexion was significantly decreased the normal walking condition (M = -23.96, SD = 3.33) compared to the stiff ankle walking condition (M = -15.05, SD = 3.34), $t(7) = -5.477$, $p < 0.05$ (Table 2).

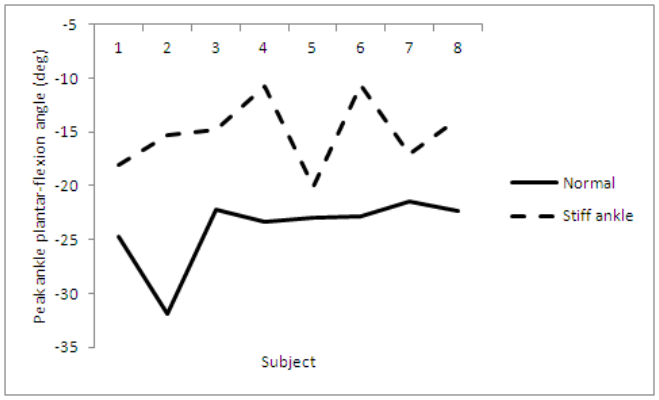

Figure 3. Peak ankle plantar flexion during initial swing compared between the normal and stiff ankle trials for each subject. Ankle movement was restricted in all subjects in the stiff ankle condition.

PTAIS values were significantly higher in the stiff ankle condition (M = 33.10, SD = 5.12) compared to the normal walking condition (M = 29.47, SD = 5.75; $t(7) = 4.32$, $p = 0.003$, two-tailed, Figure 4). There was a large effect size (eta squared = 0.853). TTAFS values were significantly lower in the stiff ankle condition (M = 0.42, SD = 0.02) compared to the normal walking condition (M = 0.44, SD = 0.03; $t(7) = -2.54$, $p = 0.039$, two-tailed, Figure 5). There was a large effect size (eta squared = 0.693). Walking speed and hip and knee kinematics were not altered between the conditions. Ankle kinematics, PTAIS and TTAFS were changed between the conditions (Tables 1 & 2).

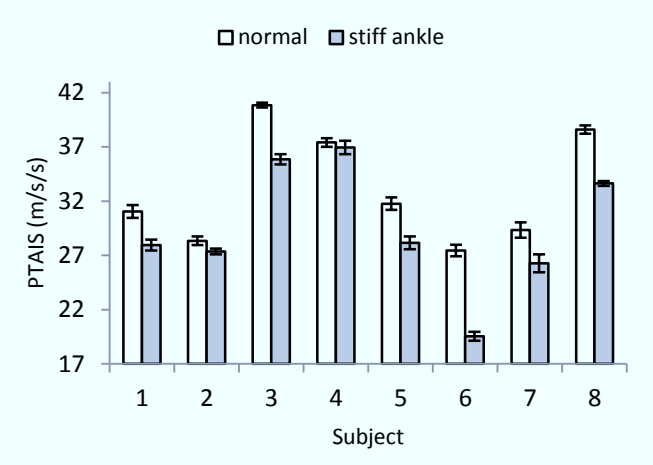

Figure 4. Change in PTAIS for each subject from the normal walking condition to the stiff ankle walking condition. Error bars show standard deviations.

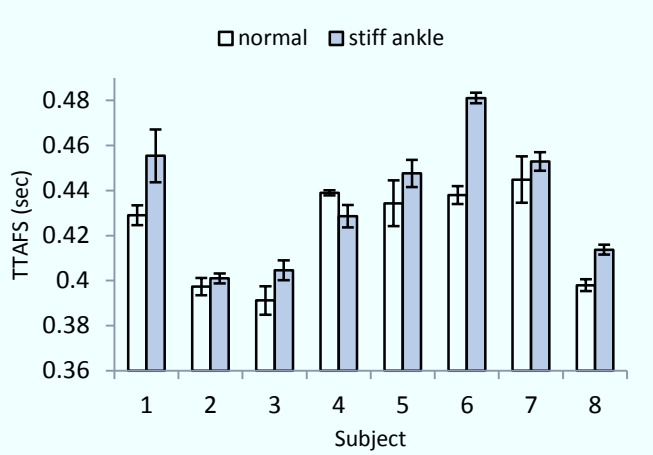

Figure 5. Change in PTAIS for each subject from the normal walking condition to the stiff ankle walking condition. Error bars show standard deviations.

TABLE I. TOTAL ACCELERATION AND SPATIO-TEMPORAL GAIT METRICS

	PTAIS*	**TTAFS***	**Speed**	**Stride length**	**Stride time**
Units	m s-1 s-1	sec	m s-1	m	sec
Stiff ankle	29.47 (5.74)	.436 (.028)	1.35 (.204)	1.493 (157.6)	1.12 (.103)
Normal walking	33.01 (5.12)	.421 (.022)	1.43 (.141)	1.535 (118.2)	1.08 (.068)

Mean values per group (SD), ** indicates significant difference between groups

TABLE II. KINEMATIC GAIT METRICS

	Peak ankle plantar-flexion *	**Peak ankle dorsi-flexion stance**	**Peak ankle plantar-flexion ang velocity***	**Peak ankle dorsi-flexion angular velocity***
units	deg	deg	deg s-1	deg s-1
Stiff ankle	-15.03 (3.37)	10.21 (4.76)	-25.63 (5.87)	14.48 (2.96)
Normal walking	-23.96 (3.33)	11.54 (4.17)	-35.07 (6.85)	20.15 (3.76)

Mean values per group (SD), ** indicates significant difference between groups

IV. Discussion

The main finding of this study is that simple to process metrics from tri-axial accelerometer data on the foot show potential to be used to detect changes in ankle movement patterns. Walking kinematic patterns were altered in the stiff ankle condition; peak ankle plantar flexion around toe-off was significantly reduced compared to the normal walking condition. Peak ankle angular velocities during the gait cycle were also significantly reduced in the stiff ankle condition. PTAIS was significantly higher and TTAFS was significantly shorter in the stiff ankle condition. The changes in kinematics and foot acceleration data were not due to different walking speeds between the two conditions. Walking speed between the two conditions was not significantly different.

In the discussion the functional implications of the changes detected in the stiff ankle condition will be discussed. Then the reasons why this research is relevant will be presented and the final point will address how this research relates to other research in the area.

A. Functional implications

Limiting the range of motion at the ankle in the stiff ankle condition resulted in subjects having significantly higher PTAIS values as measured by the accelerometer. The decreased range of motion at the ankle may have resulted in plantar-flexion coming to a stop more quickly than in the normal walking condition, resulting in increased deceleration. This would show up as larger values on the TA curve since it is an indication of the magnitude of acceleration in any direction. Hip and knee kinematics were not significantly altered in the stiff ankle condition, so the large PTAIS value of the stiff ankle condition is not due to compensatory movements by proximal joints.

TTAFS was shorter in the stiff ankle condition. This was likely due to the fact that the limited plantar-flexion range of motion meant that TO occurred earlier in the gait cycle and the foot had less distance to travel to FS.

B. Context

Preliminary results from this study indicate that PTAIS and TTAFS may be able to detect a limited ankle joint range of motion. For such an application, specific kinematic data appears not to be necessary, as long as an altered gait pattern can be identified. Such a change could warn a patient or a clinician that an altered gait pattern has emerged and a more in-depth check up is necessary to figure out what the cause is. Neuromuscular diseases that have been shown to sometimes result in limited ankle range of motion include; Parkinson's disease, stroke and diabetes mellitus [14, 15]. Ankle sprains and injuries would also result in abnormal ankle activity during walking and tracking injury rehabilitation progression may be useful using the methods described here.

Monitoring movements such as the ankle pattern is essential in the management of children with cerebral palsy and has been shown to be essential in decision making process prior to orthopedic surgical procedures [20]. A ubiquitous monitoring tool such as an accelerometer in the shoe would allow for daily monitoring, as opposed to a laboratory assessment which is costly and likely to be months or years apart.

Many studies on using inertial sensor technology to quantify human movement utilize some combination of accelerometers, gyroscopes and magnetometers [11, 12]. Data from an accelerometer alone was used in this study because accelerometers are inexpensive, small and require little processing. It is important to consider how to determine quality of movement information using as few sensors as possible because patients are more likely to use a system if it requires fewer sensors [1, 2]. The algorithm to process data presented in this paper is a simple algorithm that requires very little processing compared to algorithms that attempt to remove gravity and solve for global co-ordinate axes [11, 16]. This is an important factor for long term monitoring of gait because less processing results in longer battery lives for the sensors or local smart-phones that are processing the data.

C. Relationship to other research

The technique discussed in this research is intended toward long-term monitoring scenarios. Pedometers and accelerometers are two of the most commonly used tools in long -term monitoring studies [17, 19]. Research is mainly focused on step-counting, activity recognition or calorie consumption estimation. While these are all very useful metrics, it is not known if they are affected by subtle changes in gait patterns which may indicate early on-set disease or injury development. Preliminary data from our study under a constrained gait condition indicates that data from a shoe mounted accelerometer can be used to identify that an altered gait pattern has emerged.

Previous work has attempted to estimate lower limb joint kinematics using a regression equation with data from a shoe mounted IMU [4]. They found that this approach worked well if regression equations could be developed for each subject individually, which required subjects to initially walk in a biomechanics laboratory with optical markers and shoe mounted IMUs. This individual calibration is costly and time consuming, which limits the use of such a technique. Only normal, healthy gait was tested, so it is unclear how such a method would work if a subject were to walk at different speeds, or with different motor patterns due to disease or injury development. The technique presented in this paper does not involve any patient specific calibration.

Previous research using wearable sensor technology to monitor gait patterns over time has measured stride length from a lumbar mounted accelerometer to detect changes in the medicated state of Parkinson's patients [13]. Stride length changed by more than 0.1m, which is a large amount. Kinematic gait patterns can change while stride length remains relatively stable. In our study lower body kinematics changed from the normal to the stiff ankle condition, while stride length changed by only 0.042m on average, as Table 1 shows. Stride length alone likely has a limited role in ubiquitous gait monitoring to detect more subtle changes in gait patterns, which may indicate early on-set injury or disease development.

A limitation from this study is that the constrained gait condition was artificially induced and was not a result of an actual disease or injury. For this reason, these results must be considered preliminary until further work is done on an injured or diseased population.

The main finding of this study is that preliminary results show that simple to process data from a shoe mounted accelerometer can be used to identify an abnormal ankle movement pattern during walking.

ACKNOWLEDGMENT

This work was supported by Science Foundation Ireland under grant 07/CE/I1147.

REFERENCES

[1] Aminian K, De Andres E, Rezakhanlou K, Fritsch C, Schutz Y, Depairon M, Leyvraz PF,Robert P. Motion analysis in clinical practice using ambulatory accelerometry. *Modelling and Motion Capture Techniques for Virtual Environments,* 1998;1537):1-11.

[2] Bergmann JHM,McGregor A. Body-Worn Sensor Design: What Do Patients and Clinicians Want? *Ann. Biomed. Eng.,* 2011):1-14.

[3] Field AP. *Discovering statistics using SPSS* SAGE publications Ltd(London); 2009.p 56-57, 332-333.

[4] Findlow A, Goulermas JY, Nester C, Howard D,Kenney LPJ. Predicting lower limb joint kinematics using wearable motion sensors. *Gait Posture,* 2008;28(1):120-126.

[5] Greene BR, McGrath D, O'Neill R, O'Donovan KJ, Burns A,Caulfield B. An adaptive gyroscope-based algorithm for temporal gait analysis. *Med. Biol. Eng. Comput.,* 2010;48(12):1251-60.

[6] Hanlon M,Anderson R. Real-time gait event detection using wearable sensors. *Gait Posture,* 2009;30(4):523-527.

[7] Hartmann A, Luzi S, Murer K, de Bie RA,de Bruin ED. Concurrent validity of a trunk tri-axial accelerometer system for gait analysis in older adults. *Gait Posture,* 2009;29(3):444-448.

[8] Jasiewicz JM, Allum JHJ, Middleton JW, Barriskill A, Condie P, Purcell B,Li RCT. Gait event detection using linear accelerometers or angular velocity transducers in able-bodied and spinal-cord injured individuals. *Gait Posture,* 2006;24(4):502-509.

[9] Kotiadis D, Hermens H,Veltink P. Inertial Gait Phase Detection for control of a drop foot stimulator:: Inertial sensing for gait phase detection. *Medical Engineering & Physics,* 2010;32(4):287-297.

[10] LeMoyne R, Coroian C, Mastroianni T,Grundfest W. Accelerometers for quantification of gait and movement disorders: a perspective review. *Journal of Mechanics in Medicine and Biology,* 2008;8(2):137.

[11] Luinge H,Veltink P. Measuring orientation of human body segments using miniature gyroscopes and accelerometers. *Med. Biol. Eng. Comput.,* 2005;43(2):273-282.

[12] Mayagoitia RE, Nene AV,Veltink PH. Accelerometer and rate gyroscope measurement of kinematics: an inexpensive alternative to optical motion analysis systems. *J. Biomech.,* 2002;35(4):537-542.

[13] Moore ST, MacDougall HG, Gracies J-M, Cohen HS,Ondo WG. Long-term monitoring of gait in Parkinson's disease. *Gait Posture,* 2007;26(2):200-207.

[14] Mueller MJ, Minor SD, Sahrmann SA, Schaaf JA,Strube MJ. Differences in the gait characteristics of patients with diabetes and peripheral neuropathy compared with age-matched controls. *Physical Therapy,* 1994;74(4):299-308.

[15] Nadeau S, Gravel D, Arsenault AB,Bourbonnais D. Plantarflexor weakness as a limiting factor of gait speed in stroke subjects and the compensating role of hip flexors. *Clin. Biomech.,* 1999;14(2):125-135.

[16] Picerno P, Camomilla V,Capranica L. Countermovement jump performance assessment using a wearable 3D inertial measurement unit. *Journal of Sports Sciences,* 2011;29(2):139-146.

[17] Resnick B, Nahm ES, Orwig D, Zimmerman SS,Magaziner J. Measurement of activity in older adults: reliability and validity of the Step Activity Monitor. *Journal of nursing measurement,* 2001;9(3):275-290.

[18] Rueterbories J, Spaich EG, Larsen B,Andersen OK. Methods for gait event detection and analysis in ambulatory systems. *Medical Engineering & Physics,* 2010;32(6):545-552.

[19] Talbot LA, Gaines JM, Huynh TN,Metter EJ. A Home Based Pedometer Driven Walking Program to Increase Physical Activity in Older Adults with Osteoarthritis of the Knee: A Preliminary Study. *Journal of the American Geriatrics Society,* 2003;51(3):387-392.

[20] Wren TAL, Otsuka NY, Bowen RE, Scaduto AA, Chan LS, Sheng M, Hara R,Kay RM. Influence of gait analysis on decision-making for lower extremity orthopaedic surgery: Baseline data from a randomized controlled trial. *Gait Posture,* 2011;34(3):149-153.

[21] Yang GZ. *Body sensor networks* Springer(New York); 2006.p 4-13.