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Using a shoe mounted tri-axial accelerometer to detect kinematic changes during stiff ankle walking

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Abstract— **Ubiquitous analysis of gait is a rapidly emerging field in which research and commercial development has been focused mainly on determining spatio-temporal parameters. In this preliminary research we have developed an algorithm to determine gait metrics from a shoe mounted accelerometer and compared them with concurrent kinematic data. Subjects were tested at different walking speeds as well as an artificially induced stiff ankle condition, to determine what metrics estimate kinematic changes that are related to speed and those that are related to real kinematic changes. These preliminary findings suggest that accelerometer outputs from the foot combined with contextual knowledge of the general walking speed of the subject can be used to estimate ankle plantar flexion angular velocity in terminal stance.**

I. Introduction

Gait analysis can provide a detailed insight into the nature of deviations from normal motor programming and movement control that can occur in the presence of disease or injury [1]. Until recently gait analysis was primarily performed in a laboratory setting using marker based systems. The increasing availability of inexpensive sensor technologies has led to a large body of work directed towards development and validation of inertial sensor based gait analysis techniques [2]. Due to their simplicity, shoe mounted accelerometers offer a large opportunity to ubiquitously monitor gait in order to detect the early onset of diseases or injuries and changes in disease symptoms.

Much research has been done to investigate the feasibility of using foot mounted accelerometer data to measure spatio-temporal gait parameters [3, 4]. Other research in using accelerometers to quantify gait patterns has utilized a lumbar mounted accelerometer to estimate speed, incline and symmetry [5, 6]. Inertial measurement units (IMUs), which are accelerometers combined with gyroscopes, have been used to determine kinematic data. While this is a useful technique in a research setting it requires a person to wear so many sensors that the regular, everyday use of such systems would likely not be feasible [7, 8]. In this research we attempt to use a single sensor and computationally light data processing to estimate two important gait kinematic factors; ankle plantar-flexion and knee flexion.

The ankle plantar-flexor muscles play an important role during walking gait; they generate a large portion of the energy needed to move the limbs forward during the push-off phase [9].

Diseases that often result in abnormal plantar-flexion activity include Parkinson's disease, stroke, diabetes mellitus and cerebral palsy [10, 11]. The development of a lower body injury would also likely result in abnormal plantar-flexion activity during walking gait.

Knee flexion is important during the gait cycle because it is responsible for ensuring that the foot is in a position in which it will clear the floor during mid-swing [1]. Neuro-degenerative diseases such as Parkinson's disease often result in decreased knee flexion at initial swing; which can lead to a fall [12].

Early detection of a change in ankle plantar-flexor activity or knee flexor activity may be able to be ubiquitously detected using a tri-axial accelerometer mounted in a patient's shoe.

In this study we present an algorithm to quantify variables from shoe mounted tri-axial accelerometer data and investigate how well they relate to peak knee flexion angular velocity around TO and ankle plantar-flexion angular velocity during terminal stance. This has been achieved by means of comparing accelerometer data against kinematic data derived from a marker based gait analysis system during different walking speeds and conditions in healthy adult volunteers.

II. Methods

A. Study set-up

Eight volunteer participants were recruited for this study; 6 were female and 2 were male. Each participant signed a consent form prior to their participation and ethical approval for the study was approved by the University ethical review board. The participants' average age was 27.4 years (+/- 2.67 yrs), their average weight was 59.1 kgs (+/- 12.4 kgs) and their average height was 1.68 m (+/- 0.11m).

Each subject performed 20 separate 15m walking trials in a biomechanics laboratory. Five walking trials were taken under each of four different conditions; normal walking, fast walking, slow walking and simulated stiff ankle walking. For the fast and slow walking trials the subjects were instructed to walk at a pace that they subjectively rated as *fast* or *slow* as compared to their comfortable normal walking pace. The stiff ankle condition was simulated by using a lace up ankle brace, which restricted ankle plantar-flexion.

A CODA motion capture system (Charnwood Dynamics,

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Leicestershire, UK) was used to collect kinematic data. Markers were placed on the particiapants right and left sides at PSIS', ASIS', greater trochanters, femoral condyles, fibular heads, lateral malleoli, heels and toes. An IMU (Xsens MTx , Enschede, Netherlands) was placed on top of each subjects shoe above the shoe laces, held in place with athletic tape.

B. *Data analysis*

Data from the Xsens MTx sensors was analyzed using MATLAB 2009b (Mathworks, Massachusetts, USA). Total acceleration (TA) was calculated from x, y and z acceleration signals by using equation 1.

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

Total acceleration and x-accelerations were used to quantify the acceleration data. X-acceleration represents the sagittal plane acceleration while a subject is standing still with the sensor mounted on the dorsum of their foot. Forwards represent the positive direction. It was decided to keep the x-acceleration in local orientation in relation to the sensor. This dramatically increases the usability of these variables in a real world setting, since they do not rely on computationally heavy acceleration re-orientation into a global state. This is an important consideration, especially since for a system such as this to function in the real world there is limited processing capability on board the sensors themselves and the smart-phones that would be collecting the data.

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 foot strike (FS) occurred. Initial swing peaks were found in a range around the positive going zero crossing point and FS was found by first searching for a peak on the derivative of y-acceleration (jerk) and then finding the next peak on y-acceleration from that point. Y-acceleration represents the vertical acceleration, upwards is the positive direction.

Four main variables were determined from the accelerometer data. Peak TA during initial swing (PTAIS) and peak x-acceleration during initial swing (PAxIS) were determined and represent the maximal amount of acceleration the foot experiences during initial swing. Mean TA during mid-swing (MTAMS) shows the mean amount of acceleration seen during the swing phase. The time between peak TA during initial swing to FS (TTAFS) was also quantified and possibly has a scalar relationship to air time.

The kinematic variables determined were peak knee flexion angular velocity around TO (KFTO) and peak ankle plantar flexion angular velocity in terminal stance (APFSt). Table 1 provides a summary of all variable abbreviations.

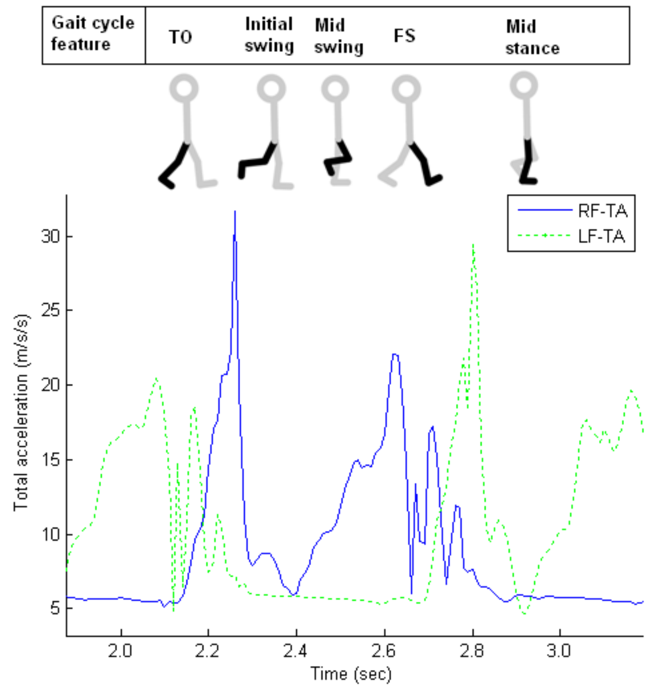

Fig. 1. Total acceleration (TA) curve for one gait cycle. RF - right foot, LF - left foot.

The relationship between the accelerometer variables and the lower body angular velocities were investigated using Pearson product-moment correlation coefficient.

TABLE I
ABBREVIATIONS

Accelerometer variables		Units
PTAIS	Peak TA during initial swing	m/s/s
PAxIS	Peak x-accel during initial swing	m/s/s
MTAMS	Mean TA during mid-swing	m/s/s
TTAFS	Time between peak TA initial swing to FS	sec
Kinematic variables		
KFTO	Peak knee flexion angular velocity around TO	deg/sec
APFSt	Peak ankle plantar flexion angular velocity in terminal stance	deg/sec

m = meter, s = second, deg = degree

Walking speed was assessed post test by calculating the stride length and stride time from the right heel marker. Multiple regression was used with walking speed category to estimate APFSt. Walking speed was categorized into normal, slow and fast and was determined from the kinematic data.

III. Results

Table 2 shows the Pearson product-moment correlations between KFTO, MTAMS and PAxIS. There was a moderate positive correlation between KFTO and mean TA mid swing ($r = 0.526$, $r^2 = 0.277$) and a moderate negative correlation to peak x-acceleration during initial swing ($r = -0.481$, $r^2 = 0.231$) [13].

TABLE II
CORRELATIONS BETWEEN KFTO AND ACCELEROMETER OUTPUTS

Kinematic variable	Algorithm output	r	r^2
KFTO	MTAMS	0.526	0.277
	PAxIS	-0.481	0.231

Figure 2 shows the relationship between PAxIS and KFTO.

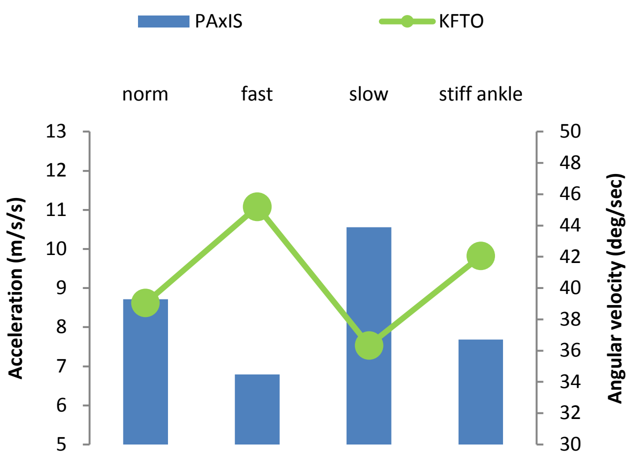

Fig. 2. The relationship between PAxIS and KFTO

A multiple regression equation was developed to estimate APFSt. This included PTAIS, MTAMS and two dummy variables; one called *fast* which was set to *1* if the person was walking fast and set to *0* if the person was not walking fast. The other dummy variable was called *norm* and was set to *1* if the person was walking at normal speed and set to *0* if the person was not walking at normal speed. The regression equation had a strong positive correlation to APFSt ($r = 0.795$, $r^2 = 0.539$). Table 3 shows the coefficients for the multiple regression equation.

TABLE III
MULTIPLE REGRESSION COEFFICIENTS FOR ESTIMATING APFSt

	B	SE B	*Beta*
Constant	-56.247	11.363	
Norm	5.959	1.244	.358*
Fast	7.229	2.114	.368*
PTAIS	-.533	.130	-.422*
TTAFS	94.439	12.877	.499*
MTAMS	-.319	.426	-.095

$r = .795$, $r^2 = .539$, * $p < .05$

Figure 3 shows the estimated APFSt from the regression equation and the actual APFSt.

IV. DISCUSSION

A. Knee flexion

KFTO was increased in the stiff ankle condition from the normal walking condition, despite the walking speed being similar in both conditions. This may be due to the fact that the knee flexors had to do more work to flex the knee, rather than rely on the power transfer from the ankle plantar-flexors, which were restricted from moving into their optimal position around TO due to the ankle brace.

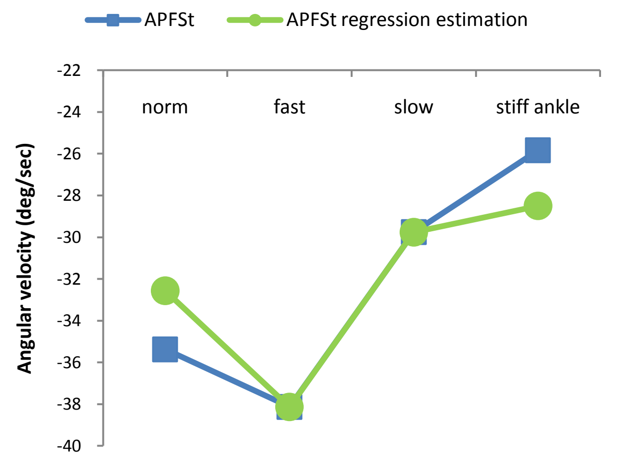

Fig. 1. APFSt plotted with APFSt estimated by the multiple regression equation.

PAxSW and MTAMS both have moderately positive correlations to KFTO. When looking at the averaged data for all subjects, it seems that PAxIS alone can detect the KFTO change in the stiff ankle condition. While this moderate relationship is interesting, it is by no means a close enough relationship to suggest that clinicians could use such measures. KFTO cannot be estimated accurately enough by using outputs from a shoe mounted accelerometer.

B. Ankle plantar flexion

APFSt was predicted by PTAIS, TTAFS and MTAMS quite well for the normal, fast and slow walking conditions, but they could not predict the lower APFSt in the stiff ankle condition. This suggests that these variables were showing changes due to speed and not due to actual ankle plantar-flexion characteristics.

However, being able to classify the subjects walking speed into normal, fast or slow allowed us to develop a regression equation which predicted APFSt well at the three different speed conditions as well as the stiff ankle condition. TTAFS had the highest coefficient in the multiple regression equation; reflecting the importance of this variable in differentiating between the different walking speeds. TTAFS alone could not predict APFSt because it is a temporal parameter that is mainly related to walking speed and walking speed was similar between the normal and stiff ankle walking conditions. Angular kinematics changed in the stiff ankle condition, but not walking speed. The downside to this regression equation is that walking speed has to be quantified.

Four main methods could potentially be used to classify walking speed in a practical setting. The addition of a single axis gyroscope to the foot sensor could allow for speed determination [14, 15]. The advantage of this is that no more sensing units are required as a gyroscope would have to be added to the accelerometer unit. The disadvantage is that processing power to calculate walking speed is much more computationally heavy than the algorithm described here and would likely result larger processor demands and shorter battery lives for the small wireless sensors involved.

A second lumbar mounted sensor could be used to estimate walking speed [5, 6]. This has the advantage of not requiring a significantly large amount of processing, since simple estimation equations can be used to determine walking speed. The disadvantage of a lumbar sensor is that it is adding another sensor to the system; one that might not be as ubiquitous as a sensor embedded in a shoe. This may decrease the usability of the system.

Thirdly, walking speed could be estimated from a GPS signal form the local smart-phone. It is likely that if such a sensing system were to be created, the shoe embedded sensor would already be communicating wirelessly with a smart-phone. Many smart-phones have GPS and walking speed could be assessed using the GPS in the smart-phone. This is an ideal scenario, except that GPS reception is not always reliable, especially in and around buildings so it may not work all the time.

Fourthly, change in MTAMS is somewhat related to walking speed and it could potentially be used to classify walking speed. This was assessed with the preliminary data in this study and it was found that comparing MTAMS to MTAMS in normal walking predicted APFSt change in the three different speed conditions, but slightly underestimated APFSt in the stiff ankle condition. Research on a larger subject pool may be useful to determine if a general trend exists that would allow for easy gait speed classification from this method.

C. Practical considerations

This research shows that APFSt cannot be estimated without knowing the general walking speed of the person. This at first may seem like a limiting factor to the usefulness of such a technique. However, walking speed classification is an important contextual factor to consider for any ubiquitous gait analysis tool. If speed classification was not known a gait problem could be erroneously flagged which was actually only due to a change in walking speed. So, for such a technique to be used in the real world, general walking speed would have to be measured regardless if it was used to aid in angular kinematic estimation.

Data from an accelerometer only was used in this study because using an accelerometer alone is cheaper, smaller and requires less processing capacity than combining it with other sensors, such as a gyroscope. These are all important considerations when researching practical methods of ubiquitous gait monitoring because if a change in movement patterns can be detected with the smallest, cheapest sensor then such a system is significantly easier to implement than a multi-sensor approach.

With the cost and size of sensor and processing technology rapidly decreasing and wireless communication becoming more efficient it is possible to envisage a system in which a tri-axial accelerometer is embedded in a shoe and communicates wirelessly with a local smart-phone which can detect if there is a change in the way a person is walking. Similar systems are available commercially, but are limited to looking at spatio-temporal parameters. Such a system may be able to help more people if it could detect changes in more important kinematic features of walking such as changes associated with diseases affecting the motor or neuromuscular system. In this way it could be useful in early diagnosis or classification of gait deviations in the field.

V. Conclusion

This preliminary research suggests that a shoe mounted accelerometer could be used to detect a change in ankle control during gait over time in a subject. This technique does not estimate changes in knee angular kinematics very well. Future research should focus on researching this finding in a larger subject pool and testing to find out if the accelerometer data alone can identify a deviation from normal gait patterns.

References

[1] J. Perry, “Gait analysis: normal and pathological function,” *Journal of Pediatric Orthopaedics,* vol. 12, no. 6, pp. 815, 1992.

[2] J. J. Kavanagh, and H. B. Menz, “Accelerometry: A technique for quantifying movement patterns during walking,” *Gait & Posture,* vol. 28, no. 1, pp. 1-15, 2008.

[3] M. Hanlon, and R. Anderson, “Real-time gait event detection using wearable sensors,” *Gait & Posture,* vol. 30, no. 4, pp. 523-527, 2009.

[4] R. W. Selles, M. A. G. Formanoy, J. B. J. Bussmann *et al.*, “Automated estimation of initial and terminal contact timing using accelerometers; development and validation in transtibial amputees and controls,” *Neural Systems and Rehabilitation Engineering, IEEE Transactions on,* vol. 13, no. 1, pp. 81-88, 2005.

[5] W. Zijlstra, “Assessment of spatio-temporal parameters during unconstrained walking,” *European Journal of Applied Physiology,* vol. 92, pp. 39 - 44, 2004.

[6] R. Moe-Nilssen, and J. Helbostad, “Interstride trunk acceleration variability but not step width variability can differentiate between fit and frail older adults,” *Gait & Posture,* vol. 21, pp. 164 - 170, 2005.

[7] T. Liu, Y. Inoue, and K. Shibata, “Development of a wearable sensor system for quantitative gait analysis,” *Measurement,* vol. 42, no. 7, pp. 978-988, 2009.

[8] T. a. S. Cloete, C., “Benchmarking of a full-body inertial motion capture system for clinical gait analysis,” *30th Annual International IEEE EMBS Conference Vancouver, BC*, 2008, 2008.

[9] D. A. Winter, “Energy generation and absorption at the ankle and knee during fast, natural, and slow cadences,” *Clinical Orthopaedics and Related Research,* vol. 175, pp. 147, 1983.

[10] S. Nadeau, D. Gravel, A. B. Arsenault *et al.*, “Plantarflexor weakness as a limiting factor of gait speed in stroke subjects and the compensating role of hip flexors,” *Clinical Biomechanics,* vol. 14, no. 2, pp. 125-135, 1999.

[11] M. J. Mueller, S. D. Minor, S. A. Sahrmann *et al.*, “Differences in the gait characteristics of patients with diabetes and peripheral neuropathy compared with age-matched controls,” *Physical therapy,* vol. 74, no. 4, pp. 299, 1994.

[12] M. E. Morris, J. McGinley, F. Huxham *et al.*, “Constraints on the kinetic, kinematic and spatiotemporal parameters of gait in Parkinson's disease,” *Human Movement Science,* vol. 18, no. 2-3, pp. 461-483, 1999.

[13] T. D. V. Swinscow, and M. J. Campbell, *Statistics at square one*: Bmj London, 1997.

[14] A. M. Sabatini, C. Martelloni, S. Scapellato *et al.*, “Assessment of walking features from foot inertial sensing,” *Biomedical Engineering, IEEE Transactions on,* vol. 52, no. 3, pp. 486-494, 2005.

[15] K. Aminian, B. Najafi, C. Büla *et al.*, “Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes,” *Journal of Biomechanics,* vol. 35, no. 5, pp. 689-699, 2002.