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Comparing Adaptive Algorithms to Measure Temporal Gait Parameters using Lower Body Mounted Inertial Sensors

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Abstract— **The purpose of this research was to compare different adaptive algorithms in terms of their ability to determine temporal gait parameters based on data acquired from inertial measurement units (IMUs). Eight subjects performed 25 walking trials over a force plate under five different conditions; normal, fast, slow, simulated stiff ankle and simulated stiff knee walking. Data from IMUs worn on the shanks and on the feet were used to identify temporal gait features using three different adaptive algorithms (Green, Selles & Sabatini). Each method's ability to estimate temporal events was compared to the gold standard force plate method for stance time (Greene, r = .990, Selles, r = 0.865, Sabatini, r = 0.980) and double support time (Greene, r = .837, Selles, r = .583, Sabatini, r = .745). The Greene method of estimating gait events from inertial sensor data resulted in the most accurate stance and double support times.**

I. Introduction

Temporal gait parameters provide information about changes in a person's movement patterns. Research has shown that the variability of temporal gait parameters can be used to predict risk of falling as well as future mobility disability in the elderly [1, 2]. Temporal parameters can also be used to track rehabilitation progress or to assess the effectiveness of a rehabilitation program.

Traditionally, temporal gait parameters are obtained in expensive and complex biomechanics laboratories. With advancing inertial sensor technology, gait parameters can now be collected as a patient goes about their daily lives [3]. Ongoing monitoring of temporal variables in the community setting could play a role in early detection of disease, measurement of falls risk, or monitoring progression during rehabilitation. It is critical that the algorithms used to identify temporal variables are as accurate as possible to provide meaningful and clinically relevant information. Furthermore, clinicians need to know how different algorithms compare to each other in order to select the most accurate one for clinical implementation.

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Two of the most commonly referenced methods of gait event detection via inertial sensors on the lower limbs utilize rotation rate data from the shank and the foot [4, 5]. The shank rotation rate method is based on the fact that during each swing phase, the sagittal plane gyroscope will show one large spike. Toe-off (TO) is found at the minimum prior to the large spike and initial contact (IC) is found at the minimum after the large spike [4]. The foot rotation rate method is based on finding a large positive spike followed by a large negative spike on the sagittal plane foot rotation rate curve after flat foot. TO is found at the peak on the first spike and IC is found on the zero crossing after the negative spike [5].

These methods have been shown to be accurate for detecting gait events on normal people walking in the laboratory at normal speed. However, recent research has shown that an adaptive algorithm with several checks is required to detect gait events for abnormal gait or different walking speeds [6, 7].

An adaptive algorithm refers to a method of finding gait events, which takes into account the fact that walking can occur at vastly different speeds and with vastly different motor patterns. Instead of directly searching for features like traditional algorithms, adaptive algorithms have multiple checks to ensure the desired features are found in the correct area or they use different methods of feature finding for different movement patterns.

Two main adaptive algorithms have emerged from the literature. The first by Selles et al. utilizes an IMU on the lateral aspect of the shank [7]. This algorithm first estimates stride time in order to optimize filter coefficients in order to find desired features correctly for various walking speeds. The algorithm then roughly estimates gait features on the filtered curve and in small windows around the estimated point searches on the unfiltered acceleration curves to zero-in on IC and TO. The second adaptive algorithm, by Greene et al. uses sagittal plane rotation rate data from the shank and zeros in on gait features in a similar fashion as Aminian et al. describe in their paper. However, the authors adopt several checks for IC, TO and mid-swing that are all based on adaptive threshold calculations. This allows gait event detection to occur at any walking speed, even during shuffling [6].

A comprehensive comparison of algorithms to estimate gait temporal parameters is not complete without including the commonly used Sabatini method of gait event detection via sagittal plane rotation rate from the foot [5]. This algorithm was made adaptive for this study by using the adaptive component of the Greene algorithm to roughly estimate events and the Sabatini method method to zero-in on the features.

The purpose of this research is to determine which adaptive algorithm is most accurate at estimating temporal gait parameters.

II. Methods

Eight volunteer participants were recruited for the study. Six were female and two were 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).

The participants performed a total of twenty five 15m walking trials in a biomechanics laboratory. Subjects performed 5 trials under each condition. The five conditions were; normal, fast, slow, stiff ankle and stiff knee walking. Stiff ankle gait was simulated by use of a lace up ankle brace which restricted ankle plantar-flexion. Stiff knee gait was simulated by use of athletic tape over the anterior aspect of the knee to restrict knee flexion.

The stiff ankle condition was included to analyse algorithm performance with abnormal ankle movement patterns. Diseases that often result in abnormal plantar-flexion activity include Parkinson's disease, stroke, diabetes mellitus and cerebral palsy [8, 9]. The stiff knee condition was included to look at algorithm performance with abnormal knee movement patterns. Neuro-degenerative diseases such as Parkinson's disease often result in decreased knee flexion at initial swing; which can lead to and increase likelihood of a fall [10].

Two AMTI force plates (Watertown, Massachusetts) embedded into the floor of the laboratory were used as the gold standard to determine when IC and TO occurred. IC was identified when the vertical ground reaction force had an upward-going crossing at 10 N and TO was found when the vertical ground reaction force had a negative-going crossing at 10 N [11]. Stance time and double support time were calculated from the force plate data.

Four IMUs (Xsens MTx, Enschede, Netherlands) were placed on each subject. Two were placed on the dorsal aspect of the foot, with the distal edge of the sensor lined up with a line parallel to the frontal plane that intersects the 5th metatarsal. The other two sensors were placed on the anterior aspect of the tibia, with the centre of the IMU at the mid-point between the lateral malleolus and the knee joint centre. All sensors were held in place using athletic tape. Since the IMUs recorded acceleration and rotation rate in 3-axes, it is possible to obtain sagittal plane rotation rate from this sensor set up.

A. Data processing

Data was processed using MATLAB 2009b. The Greene and Selles methods of estimating gait events were replicated from the algorithms presented in their papers [6, 7]. There is no published adaptive algorithm that uses sagittal plane foot gyroscope data, so gait events were found using the Sabatini method by looking for the desired features in 20 m/sec windows around the IC and TO points from the Greene adaptive algorithm. Data from the right foot was used since the constraints were applied to that side.

B. Statistics

From each walking trial at least one stance phase was determined from the force-plate data. Depending on how the subjects other foot hit the second force plate, another stance phase as well as a double support phase was also calculated. Overall 213 stance times and 126 double support times were compared. All stance and double support times were averaged for each participant for each condition. A Bland-Altman style comparison was used to compare the three methods of gait event detection to the gold standard force-plate [12]. Pearson product correlations, mean differences and the 95% confidence intervals were calculated between the force plate and each of the event estimation methods to assess how well each algorithm estimated stance and double support times during gait.

III. Results

Table 1 shows the stance time comparison between the force plate and the various algorithms. Table 2 shows the double support time comparison between the force plate and the various algorithms.

The Selles algorithm did not work for 15 walking trails; 10 of them were stiff knee trials and 5 of them were fast walking trials.

IV. Discussion

The main finding of this study is that temporal gait parameters that are calculated from lower body inertial sensors using the Greene method of gait event detection are more accurate than temporal parameters that are calculated from the Selles or Sabatini method of gait event detection.

The Selles method of gait event detection is based on looking at changes in local accelerations at the shank. Gravity is not removed from the signal in the Selles method, so gravitational acceleration and acceleration due to movement are both present. The advantages of using local accelerations to detect gait events are twofold; firstly, using accelerometers alone is cheaper than using accelerometers combined with gyroscopes. Secondly, since the accelerometer data is kept in the local orientation, much less processing is required than if the method required gravity to be removed and the acceleration rotated to a global orientation. These are relevant considerations for deployable applications, where the processing is happening on the sensors themselves or a local smart-phone and the amount of processing affects the longevity of the battery.

TABLE I. DOUBLE SUPPORT TIME ESTIMATION COMPARISON

Stance time		*r*	Mean diff	Lower 95% CI	Upper 95% CI	CI width
Different speeds	Greene	.997	.037	.014	.060	.045
	Selles	.679	.030	-.170	.231	.401
	Sabatini	.986	.006	-.048	.061	.109
Constrained gait	Greene	.943	.050	-.018	.118	.135
	Selles	.888	.118	-.063	.108	.171
	Sabatini	.913	.023	-.059	.104	.163
All conditions	Greene	.990	.042	-.005	.090	.095
	Selles	.865	.028	-.138	.193	.330
	Sabatini	.980	.013	-.055	.081	.136

TABLE II. DOUBLE SUPPORT TIME ESTIMATION COMPARISON

Stance time		*r*	Mean diff	Lower 95% CI	Upper 95% CI	CI width
Different speeds	Greene	.856	.044	-.009	.096	.105
	Selles	.582	.014	-.049	.078	.127
	Sabatini	.888	.018	-.029	.066	.094
Constrained gait	Greene	.810	.055	.011	.098	.087
	Selles	.587	.018	-.041	.077	.118
	Sabatini	.242	.022	-.051	.095	.147
All conditions	Greene	.837	.048	-.001	.098	.099
	Selles	.583	.024	-.084	.132	.216
	Sabatini	.745	.020	-.039	.078	.117

Temporal parameters calculated from gait events found using the Selles method, were less accurate than using the other two methods. The Selles method is based on initial aggressive filtering to figure out roughly where gait events occur, then using small windows around the approximate values, looking on the unfiltered local accelerations to find specific features which represent gait events. The filter coefficients to determine approximate gait events were where this method fell down. When looking for approximate gait events the filter sometimes did not produce the desired type of curve. This was especially prevalent in the slower trials; the filter to find approximate TO was meant to produce a curve with two peaks during each gait cycle, but sometimes resulted in a curve with one peak per gait cycle or none. In 15 trials the filter resulted in such a different curve that the event estimation was deemed to be fundamentally flawed and the test was not included in the results.

It is not clear whether or not, the fine features that Selles et al. proposed as IC and TO are in fact those locations. Unfiltered acceleration signals from the shank are very noisy and different movement patterns can result in vastly different looking signals. Perhaps, creating more checks in determining the correct filter coefficient could result in a more accurate estimation, but this would only work if the fine features to zero in on exact gait events are accurate.

There is no published adaptive algorithm using the Sabatini method of gait event detection. Since the Sabatini method is so popular in the literature the authors felt it was

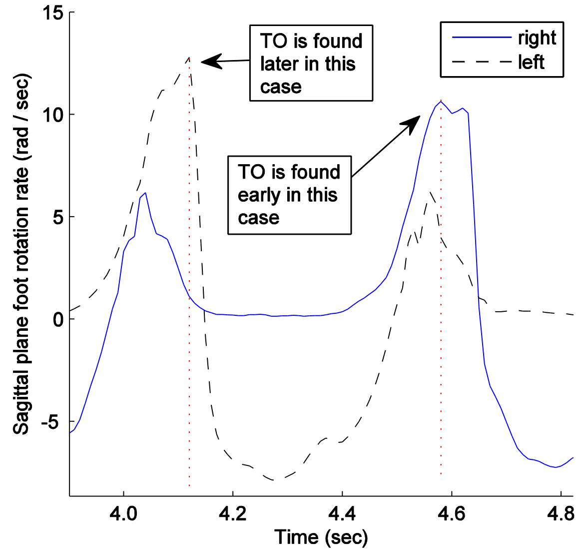

Figure 1. Sagittal plane rotation rate data from both feet. The first TO is found later on the peak, whereas the second TO is found earlier because the first hump has a higher peak value. This discrepancy is why the Sabatini method of estimating double support time is inaccurate.

important to include it in this analysis. The algorithm used in this study used the Greene adaptive algorithm to first find approximate IC and TO points and then zeroed in on IC and TO at the points described by Sabatini.

The Sabatini method of gait event detection is based on using sagittal plane gyroscope data from the foot. This location of sensor placement has the advantage of being able to be embedded into a shoe, which would not require a user to put on anything extra than their shoe and would enhance the ease of use of a deployable application. The Sabatini algorithm is nearly as good as the Greene algorithm at estimating stance time for all conditions and double support time for different speeds. However, the Sabatini method cannot reasonably estimate double support time during the constrained walking conditions.

Some subjects had a *double-hump* feature at the peak foot rotation rate where TO was found. At different times either the first peak or the second peak would be found as TO depending on which peak had a higher maximum. This inaccuracy in finding TO seems to account for the poor ability of the Sabatini method to estimate double support time because the differences between the two peaks is a large percentage of the relatively short double support time. The Sabatini method detects stance time reasonably well because this *double-hump* difference is a very small percentage of the overall stance time; one peak or the other both result in reasonably accurate data. This problem is illustrated in Fig. 1, where two successive TO's are shown. The first peak has a local maximum later and TO is found there, whereas the second peak has a local maximum earlier and TO is found there.

The Greene method of gait event detection is based on using sagittal plane gyroscope signals from the shank, which equates to the sagittal plane rotation rate from the shank. Seeing as the leg has to swing from behind the body to the front of the body for each step, there should a consistent increase in rotation rate from the shank during each step. Basing feature detection on this consistent, large feature seems to be more accurate than basing it on local accelerations or foot rotation rate data. Use of the Greene adaptive algorithm to find gait events resulted in the most accurate temporal gait parameters.

An advantage of using a shank mounted gyroscope compared to accelerometers is that, as long as the gyroscope is recording data in the correct plane, it does not matter where on the shank the sensor is placed. When using the accelerometers it is important that they are placed in the same location each time as the signal is affected by how far from the centre of rotation they are [13].

Previously published research that found that shank rotation, foot rotation and an acceleration based algorithm all estimated gait events equally well for normal, healthy gait [14]. The acceleration based method used in our study is different than the method used in the Jaisewicz study, so it is understandable how our results for healthy gait found that the acceleration method performed poorly. The shank rotation and foot rotation methods in our study were both accurate for estimating temporal parameters in normal walking at different speeds.

The Jaisewicz study found that using the shank gyroscope method was not as accurate when subjects were walking with their walking aids (crutches or walkers). This was attributed to instability or oscillations around IC and TO in that group. In the current study shank gyroscope data was accurate at estimating temporal gait features even in the constrained gait conditions. This difference in results may be due to some combination of the fact that the abnormal walking conditions in our study were artificially induced and the fact that walking with walking aids was not tested in our study.

A. Limitations

A limitation to this study is that the constrained gait conditions were artificially imposed and were not a result of actual gait problems. Another limitation is that shuffling was not tested, which is a clinically relevant type of gait since many injured and elderly persons walk that way. Also, due to limitations in the data collection it is was not possible to determine if errors in temporal parameter estimation were due to errors in IC or TO feature detection.

V. Conclusion

When designing an algorithm for a small group of homogenous subjects, a basic algorithm may work. However, applying such an algorithm to a larger, more heterogeneous group of subjects means that the algorithm must be able to take into account vastly different movement patterns. Multiple checks and possibly different feature detection strategies for different movement patterns are necessary by use of an adaptive algorithm. The adaptive algorithm proposed by Greene to detect gait events resulted in the most accurate temporal gait parameters when compared to various other adaptive algorithms.

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