A comparison of methods to detect postural transitions using a single tri-axial accelerometer

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***Abstract*— Two algorithms for evaluating postural transitions (PTs) in cohorts of 40 healthy younger and 40 older adults are described and evaluated. The time of sit-to-stand (SiSt) and stand-to-sit (StSi) transitions and their duration were measured with two tri-axial accelerometers, one on the chest and one on the lower back. Each algorithm was optimized for these sensor placements. The first algorithm for sensor placement on the chest used a scalar product and vertical velocity estimates. The second algorithm for sensor placement on the lower back used a vector magnitude and a discrete wavelet transform. Both algorithms performed excellently in PT classification for younger and older adults (>86%). However, the chest based sensor and algorithm were better for estimating transition duration (TD) with ICCs to video analysis ranging from 0.678 to 0.969.**

I. Introduction

Current research recommends the instrumentation of physical functioning tasks in clinical settings [1]. Instrumentation provides an objective and highly accurate means to test/retest individuals within or across studies. In addition instrumentation can be used to establish a standard approach for assessments thereby adopting a common currency with the potential to analyse data across studies and to facilitate the pooling of research findings [1, 2]. Traditional tests to assess physical functioning include standing balance for posture control, 2/6/10 minute walks for endurance and postural transitions for lower extremity strength. Postural transitions (PT) such as sitting-to-standing (SiSt) and standing-to-sitting (StSi) is a common physical task that can be performed many times each day and is a prerequisite for maintaining independent functioning [3].

The assessment of PT is useful clinically because PT variables are associated strongly with falls risk in healthy older adults and those with age-related pathologies [3-5]. Falling is the most common type of home accidents among elderly people [5]. Transition duration is a key feature of SiSt or StSi that has been associated with falls (or falls risk) [3]. A number of studies have used various sensor configurations (accelerometer with/without gyroscopes) and associated algorithms for both the detection of PT and for assessment of the duration of SiSt or StSi transitions [3, 5-7]. However, the use of a single sensor arrangement (leading to reduced size and cost) with a less complex algorithm remains the goal to facilitate replication and widespread use of such approaches in future studies [7, 8].

In this paper, we describe two algorithms for evaluating the characteristics of a PT and compare them with a gold standard reference. In the first instance the algorithms were evaluated for their ability to classify a PT, either as a SiSt or StSi. Secondly, the accuracy of the algorithms for estimating transition duration (TD) times were evaluated and compared directly with timed recordings from video observations. Based on these analyses, we recommend the most suitable approach to instrumenting the assessment of PT in both healthy younger and older adults.

II. Methods

A. Participants

Forty healthy young adults aged 20-40 years (YHP) and forty healthy older adults (OHP) were recruited. Participants were recruited from staff and students at Newcastle University and members of Newcastle University VOICENorth, an older volunteer group who participate in research. Participants were recruited only if they had no physical or neurological disability that might impede their movement. All participants gave written informed consent and ethical consent was granted by the National Research Ethics Service (County Durham and Tees Valley).

B. Equipment

Each participant wore two Axivity AX3 accelerometer-based sensors (Axivity, York, UK) - one located on the lower back (lumber vertebrae, L5) and one centrally on the sternum (chest), Figure 1(a). The sensors were held in place by double sided tape and Hypafix (BSN Medical Limited, Hull, UK). The sensors were programmed to capture at 100-Hz (16-bit resolution) and at a range of ±8g. Recorded accelerations were stored locally on the sensor's internal memory as a raw binary file that was downloaded upon the completion of each trial. Video recording was performed during each trial and used as the gold standard reference to validate the type of PT (SiSt or StSi) and the estimated TD from each algorithm.

C. Experimental protocol

Calibration of the tri-axial accelerometer was performed using previous methods as outlined by Ferraris et al [9] and has also been adopted in other studies [7, 10]. Briefly, participants were asked to remain still prior to the beginning

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and at the end of each postural transition trial to account for any offsets in the accelerometer signal. A researcher used video play back to manually note the starting and end time of each PT, the gold standard. For the purposes of this study, the TD for SiSt was defined as the period from when the participant began to move their torso until they had reached a static state in an upright standing position. Conversely, StSi was defined as the period from when the participant began to move from a static upright position to the moment of equilibrium in a seating position.

The participants performed 3 × SiSt and 3 × StSi trials from 2 different chairs of similar height:

- Chair #1: height 41cm with arm rests. Height to arm rest 66cm. The participants were instructed to use the arm rests if they wished.
- Chair #2: height 43cm with no arm rests.

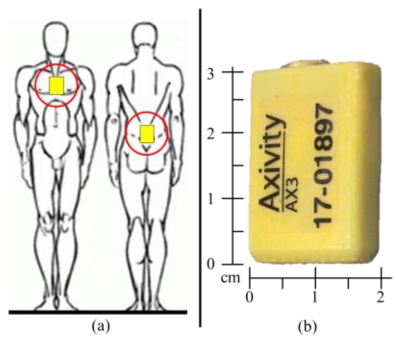

Figure 1. (a) Attachment of the Axivity sensor to the chest and L5 and (b) the Axivity sensor with its dimansions

D. Algorithms

After testing, data were downloaded to a computer and analysed using a specially written MATLAB program. Two PT algorithms were implemented in this study, both optimised for specific sensor locations: one on the chest and one for the lower back (L5). The algorithms consisted of the following:

- Chest: for the classification of a PT the *VESPA* algorithm was implemented [7]. This algorithm adopts two techniques: scalar product, the multiplication of a row (*a*) and column (*b*) vectors (1) and vertical velocity estimates, the numerical integration of the norm of the tri-axial acceleration signals (a_x, a_y, a_z) after gravity is subtracted (2). To calculate TD, the time of the PT (t_{PT}) is determined from the scalar product of the acceleration signals. The scalar product is used to estimate trunk tilt [7] for which purpose, gyroscopes have been used previously [5]. Once t_{PT} was determined, TD was estimated from the time between the peaks immediately before/after t_{PT}, Figure 2. Then to classify the type of PT (SiSt or StSi), the shape of the vertical velocity estimates around the time of t_{PT} were examined [7].

$$\theta_N = \cos^{-1}\frac{(a \cdot b_N)}{|a| \cdot |b_N|} \tag{1}$$

$$v_{ve} = \int \left(\sqrt{a_x^2 + a_y^2 + a_z^2} - 9.81\text{ms}^{-2}\right) dt \tag{2}$$

- L5: The second method used to detect and estimate TD was that described by Bidargaddi et al [6]. Firstly, this method calculated the signal vector magnitude (SVM) from a combination of all three axes of the accelerometer. Then in accordance with the algorithm, a discrete wavelet transform (DWT) was used to extract the 5th order approximation of the SVM using a discrete Meyer (mother) wavelet, ψ, sampled at discrete point's k and l (3). The TD was estimated from the time between the negative and positive peaks, Figure 3. Since that time is only half the duration required for TD, the estimates were multiplied by 2 to provide the final TD estimation. The type of PT was determined from the order of the peaks [6].

$$x(t) = \sum_{k=-\infty}^{\infty}\sum_{\ell=-\infty}^{\infty} d(k,\ell)2^{-k/2}\psi(2^{-k}t - \ell) \tag{3}$$

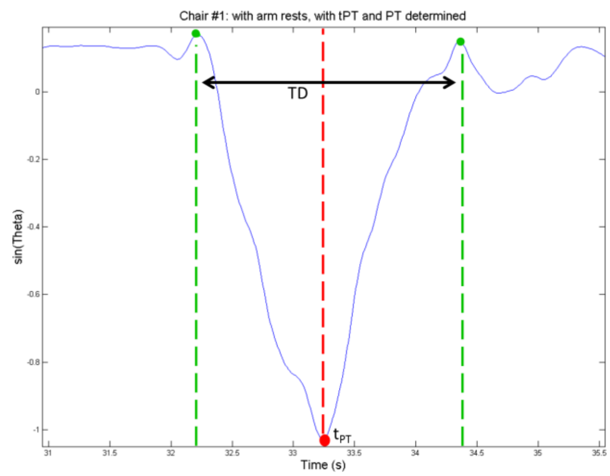

Figure 2. Estimation of t_{PT} and TD time from the VESPA algorithm with the sensor located on the chest. In this example the PT was performed by a OHP using chair #1.

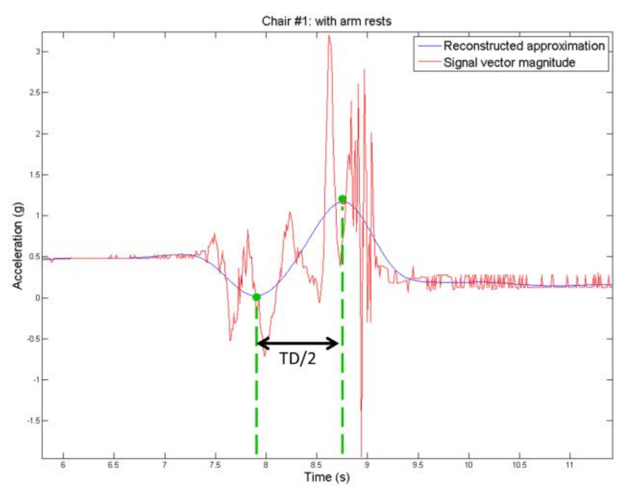

Figure 3. Estimation of half the TD time from the wavelet algorithm with the sensor location on L5. Here, the PT was performed by a YHP using chair #1.

E. Statistical analysis

Mean and standard deviations were calculated for each PT trial for both YHP and OHP. The normality of data distributions was tested with a Shapiro-Wilk test. Bland-Altman plots were generated to provide a visual representation of agreement between systems (accelerometer-based estimates and those from the "gold standard" video recordings) by plotting the individual participant difference for the two systems against the mean estimate for that individual derived from both systems. Limits of agreement (LoA) between the gold standard reference (video) and sensor location with associated algorithm were expressed as intraclass correlation coefficients (ICCs) of type (2,k). Limits of agreement are expressed in absolute terms as well as percentage of the group mean. The statistical significance was set at $p<0.05$.

III. Results

One L5 sensor failed to record in the YHP group and 3 (1 chest and 2 L5) in the OHP group and, as a result, data for direct comparison between the systems were available from 39 YHP and 37 OHP. Table I shows the participant characteristics.

TABLE I. PARTICIPANT CHARACTERISTICS

Characteristic	YHP (N=39)	OHP (N=37)
Gender (M/F)	20 / 19	14 / 23
Age (years)	28.79 ± 5.29	63.07 ± 6.37
Height (cm)	172.12 ± 8.81	166.14 ± 9.41
Weight (kg)	72.81 ± 13.89	71.20 ± 15.17

A. PT detection

In total 117 (39 × 3) SiSt and StSi PT were performed by the YHP. The VESPA algorithm classified correctly 109 (93.16%) SiSt and 115 (98.29%) StSi PT for chair 1 and 117 (100.00%) SiSt and 116 (99.15%) StSi PT for chair 2. In contrast the Wavelet algorithm classified correctly 117 (100.00%) SiSt and 116 (99.15%) StSi PT using chair 1 and 113 (96.58%) SiSt and 111 (94.87%) StSi PT using chair 2.

The OHP performed 111 (37 × 3) SiSt and StSi PT. The VESPA algorithm classified correctly 96 (86.49%) SiSt and 108 (97.30%) StSi PT for chair 1 and 110 (99.10%) SiSt and 110 (99.10%) StSi PT for chair 2. The wavelet algorithm classified correctly 104 (93.69%) SiSt and 103 (92.79%) StSi PT using chair 1 and 100 (90.09%) SiSt and 96 (86.49%) StSi PT using chair 2.

B. Limits of agreement

Table II summarises the descriptive data obtained using the VESPA algorithm for the YHPS and OHP. There is excellent agreement between the video recording and the VESPA algorithm for the SiSt and StSi TD times for both chairs in the YHS group (ICCs, 0.918-0.969) while only moderate for the OHS (ICCs, 0.678-0.772). Mean differences (MD) showed there was a systematic over estimation of the TD times in both YHS and OHS.

For the YHP, the range for the 95% limits of agreement is 0.8 (±0.40) seconds with LoA of between 18.3 and 26.9%, Figure 4(a). For the OHP, the 95% limits of agreement increased to almost 2.0 seconds with higher LoA ranging from 33.3 to 49.9%.

TABLE II. VESPA ALGORITHM: DESCRIPTIVE PT DATA FOR THE YHP AND OHP SHOWING THE MEAN AND STANDARD DEVIATION OF TD, MEAN DIFFERENCE ($\bar{x}$) ± 95 % AND AGREEMENT BETWEEN SYSTEMS

PT	Video (s)	VESPA (s)	LoA	$\bar{x}$ ± 95%	ICC
YHP					
SiSt 1	1.39 ±0.30	1.47 ±0.39	25.4	0.08 ±0.36	0.918
StSi 1	1.82 ±0.44	1.75 ±0.53	18.3	-0.06 ±0.33	0.965
SiSt 2	1.46 ±0.36	1.54 ±0.47	26.9	0.07 ±0.40	0.931
StSi 2	1.85 ±0.43	1.86 ±0.83	18.3	0.01 ±0.34	0.969
OHP					
SiSt 1	1.37 ±0.31	1.52 ±0.38	43.0	0.16 ±0.62	0.707
StSi 1	1.84 ±0.43	1.95 ±0.54	49.9	0.11 ±0.93	0.678
SiSt 2	1.39 ±0.27	1.53 ±0.36	33.3	0.13 ±0.48	0.772
StSi 2	1.75 ±0.34	1.80 ±0.45	39.9	0.04 ±0.70	0.754

Table III summarises the descriptive data obtained using the wavelet algorithm for the YHP and OHP. There was weaker agreement between the results obtained using the video recording and this algorithm for the SiSt and StSi TD times for both chairs in the YHP group (ICCs, 0.363-0.538) and agreement for the OHP group (ICCs, 0.144-0.523). In contrast with results from use of the VESPA algorithm, there was a systematic underestimation of TD times for both the YHP and OHP groups.

For the YHP, the 95% limits of agreement ranged as high as 1.5 (±0.75) seconds with LoA of between 37.1 and 47.7%, Figure 4(b). For the OHP, the 95% limits of agreement increased to almost 2.0 seconds with higher LoA ranging from 41.7 to 58.2%. For all PT's in both OHP and YHP, there were no clear differences in the type of chair used.

TABLE III. WAVELET ALGORITHM: DESCRIPTIVE PT DATA FOR THE YHS AND OHP SHOWING THE MEAN AND STANDARD DEVIATION OF TD, MEAN DIFFERENCE ($\bar{x}$) ± 95 % AND AGREEMENT BETWEEN SYSTEMS

PT	Video (s)	Wavelet (s)	LoA	$\bar{x}$ ± 95%	ICC
YHP					
SiSt 1	1.39 ±0.30	1.36 ±0.16	37.1	-0.02 ±0.51	0.538
StSi 1	1.82 ±0.44	1.52 ±0.28	45.4	-0.29 ±0.75	0.473
SiSt 2	1.46 ±0.36	1.37 ±0.14	41.8	-0.09 ±0.59	0.479
StSi 2	1.85 ±0.43	1.47 ±0.21	47.7	-0.37 ±0.79	0.363
OHP					
SiSt 1	1.37 ±0.31	1.40 ±0.29	50.6	0.02 ±0.70	0.512
StSi 1	1.84 ±0.43	1.58 ±0.32	58.2	-0.25 ±0.99	0.144
SiSt 2	1.39 ±0.27	1.42 ±0.23	47.8	0.03 ±0.67	0.213
StSi 2	1.75 ±0.34	1.65 ±0.33	41.7	-0.10 ±0.71	0.523

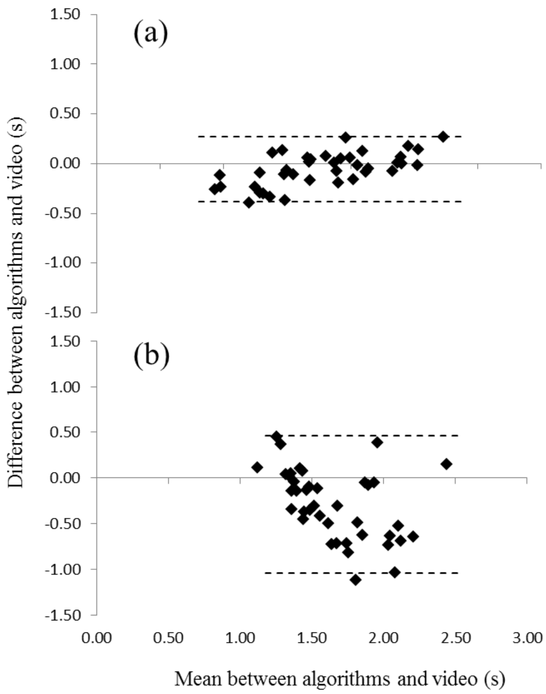

Figure 4. Bland-Altman plots of the averaged TD times for YHP using chair #1 (a) VESPA algorithm and (b) Wavelet algorithm.

IV. DISCUSSION

The aims of this study were to evaluate two algorithms for their utility in interrogating data from use of an accelerometer-based device to classify PT and to evaluate their accuracy in measuring the TD of each PT. Both algorithms were excellent in classifying the PT type (SiSt and StSi) based upon a large number of transitions performed using two different chairs in both the YHP (>93%) and OHP (>86%) groups. Results from the VESPA algorithm correlated better with those from the gold standard video recording with excellent ICCs for the YHP (0.918 - 0.969) and moderate for OHP (0.678 – 0.772). In comparison, results from use of the wavelet algorithm showed only moderate correlations for the YHP (ICCs, 0.363 – 0.538) and low correlations for the OHP (ICCs, 0.144 – 0.523). One explanation for this discordant finding is that the definition of a TD used within this study and the PT strategy adopted by the participants were better suited to data analysis using the VESPA algorithm rather than wavelet algorithm and was independent of the type of chair used. Firstly, we defined a TD for SiSt and StSi as the periods from static equilibrium in a sitting/standing position to the next period of static equilibrium. Secondly, the PT strategy adopted by the YHP and OHP for SiSt can be defined by the momentum transfer (MT) strategy, the ideal and most efficient strategy for all healthy adults [11]. During MT, the upper-body transfers forward momentum to vertical momentum and continues forward momentum until the person lifts the buttocks off the chair ('lift off') [12]. Those dynamics constitute the theoretical basis for the VESPA algorithm and are optimised for use with data from a sensor placed on the chest. In contrast, with data from a sensor placed on L5, the wavelet algorithm is not suited to detection of the initiation of forward momentum from the upper torso during a normal SiSt. Although not investigated in the present study, it is possible that the wavelet algorithm may be best suited to use with data from patients with pathologies which affect PT or older adults with functional limitations who adopt a different PT strategy such as the stabilisation strategy, where lift off from the seat is accomplished without assistance from vertical momentum [12]. This hypothesis remains to be tested.

V. CONCLUSION

The use of an accelerometer-based sensor on the chest or lower back to capture PT and the application of appropriate algorithms to interrogate the resulting datasets can provide accurate means of detection of SiSt and StSi transitions. In our experience, the VESPA algorithm with sensor location on the chest was more accurate in detecting transition duration for both sitting to standing and standing to sitting transitions in both healthy younger and older adults.

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