

*Proceedings*

Validating Temporal Motion Kinematics from Clothing Attached Inertial Sensors [†]

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Abstract: A major barrier to wearables utility for kinematic analysis is convenience. Attachment to skin requires significant expertise and is time consuming. Instead this research applies principles of sensor analysis to clothing attachments, to examine temporal immunity to clothing artefact. No known research has validated temporal outputs of inertial measurement units when embedded in clothing. Nine participants completed five repetitions of conventional deadlifts while being monitored with inertial sensors fixed on anatomical landmarks and embedded in clothing. The agreement of group means between timing outputs of inertial sensor anteroposterior axis data were compared between sensor locations. Will Hopkins Typical Error of the Estimate, Pearson's correlation and a Bland Altman Limits of Agreement analysis were implemented for validation. Strong agreement was found based on trivial standardised error (<0.1) for all agreement analyses. Results support past research for applications applying temporal features of wearables to monitor human movement.

Keywords: wearables; inertial sensor; validation; gyroscope; timing; human movement

1. Introduction

Wearable inertial measurement units (wearables) are devices that are ubiquitous in many ways and becoming readily available to populations away from research. Monitoring human movement with wearables may be more practical than other 3D motion capture methods. Micro electromechanical based inertial sensors are mainstream wearables which can house multiple devices for monitoring human movement. Wireless connectivity permits multiple sensor monitoring through software tools allowing for synchronisation between devices for data analysis or real time feedback [1]. Typical inertial sensors include gyroscopes which measure a bodies angular rate of change around an axis in degrees per second (s) which can be used to estimate absolute joint angular position in human locomotion [2]. The strength of inertial sensors includes simple user interface possibilities implemented with software, and ambulatory integration into regular clinical, sporting or organisational monitoring at low cost.

Inertial sensor magnitude outputs have been previously validated for monitoring human movement event detection and activity classification [3]. In addition to magnitude, timing outputs from inertial sensors fixed to the skin at anatomical landmarks can be used with as much confidence as 3D motion capture systems [4]. This past validation between 3D motion capture and skin mounted inertial sensors demonstrated that timing outputs from inertial sensors are comparable to true values, and can now be used as a criterion measure for further research. Temporal outputs are necessary for monitoring body segment timing during human movement and key events [5]. Inertial sensors have been used to monitor temporal parameters of human movements in various gait and sporting

contexts [6]. Furthermore inertial sensors have been implemented in working environments for ergonomic purposes such as monitoring segment motion, activity identification, and for sensor fusion applications [7]. Sensor fusion is the application of data from multiple devices to compute or measure a variable which would be less accurate or unattainable from a single device.

Workplace apparel and casual clothing are typically loose fitting and may add sensor artefact into collected data due to the large and random movement of clothing. To reduce this assumed limitation wearables are typically attached in tight fitting garments such as belts or straps. However, no known research reporting accuracy of timing outputs from wearable sensors exist, despite the potential various practical applications and pre-existing interventions implementing worn sensor devices in numerous environments [4]. Therefore before interventions are possible, supporting validation is required for clothing attachment methods to determine the influence of clothing artefact. There is currently no known published validation for monitoring timing outputs of wearable inertial sensors sewn into clothing.

The purpose of this research was to expand on previous research methods [4] by validating wearables for monitoring the timing of spinal postural changes at practical device mounting locations. The aim was to investigate the validity of timing outputs during resistance exercise from inertial sensors embedded in tight fitting sporting apparel and workplace clothing at different landmarks. This was achieved by measuring the agreement of group means between timing outputs from inertial sensors fixed on the skin and inertial sensors placed in tight fitting garments.

2. Materials and Methods

This research was approved by the institutional ethics committee at Charles Darwin University (reference number H14046). Nine volunteers (one female and eight males) sourced from the general population participated. There was a strict inclusion criteria to ensure participant safety when performing resistance exercise. Inclusion criteria included a minimum age of 18, previous experience in performing resistance exercise, and a low health risk for performing high intensity physical activity. Informed consent was obtained prior to any involvement and data collection was supervised by a qualified sport scientist to oversee that lifts were performed in a safe manner. Inertial sensors used included a tri axial accelerometer and gyroscope (SABEL Sense, Sports and Biomedical Engineering Laboratories and wearable technologies, Brisbane, Australia) [8]. These sensors are lightweight at 23 g with dimensions 55 mm × 30 mm × 13 mm [5]. Inertial sensor devices were attached to participant's skin with Physiotherapy tape at the spinal landmarks cervical vertebrae seven (C7) and thoracic vertebrae 12 (T12). This method has been successfully implemented in previous research [4,8]. An inertial sensor was sewn into a garment worn in workplaces with high manual handling exposure (high visibility workplace jacket), directly posterior to the body worn sensor located at C7. Typically jackets and upper body clothing is tighter fitting around the shoulders and neck compared to the waist or abdomen. Therefore practically C7 was the only location appropriate to attach a wearable device in the high visibility jacket due to the area being the tightest fit on participants with the least observed movement occurring. A tight fitting elastic heart rate monitor vest typically used in sport/exercise environments (heart rate monitor was removed) was also worn by participants including two inertial sensor devices in sewn in pockets, located posterior to the skin mounted sensors (same anatomical locations) at C7 and T12. Inertial sensor devices were set at 100 Hertz (Hz) and synchronised for time by connecting wirelessly to a hub device. Sensor calibration followed procedures previously reported which used gravity as the constant measured against [9]. Participants completed one set of conventional deadlifts in a controlled environment for five repetitions with no weight (broomstick) to ensure minimal risks of injury. A conventional deadlift was chosen for analysis due to representing one of the most recognised back lift and resistance exercise methods for lifting an object from the floor to hip height. The conventional deadlift is applicable to numerous contexts including sport, health and rehabilitation, occupational contexts and daily living lifting activities from the floor. Participants were asked to complete the deadlift at a comfortable speed which reflected how fast they would lift in a daily living or workplace setting. Therefore the conventional deadlift was appropriate to provide adequate data for agreement analysis.

Raw data were downloaded directly from the devices and signal processing was performed in Matlab (R2014, The MathWorks, Inc., Natick, MS, USA). A 5 Hz hamming filter was applied and the corresponding peaks in Gyroscope Y axis data for each repetition and each inertial sensor was identified. The inertial sensor Y axis was orientated on the mediolateral axis of the spine. Therefore, monitoring about the Y axis was chosen for analysis due to representing the anteroposterior (flexion and extension in the sagittal plane) movement of the spine. The duration measured in seconds (s) between peaks in angular velocity data were extracted. These data represented the time participants took to complete a single conventional deadlift. Gender data were grouped due to the analysis validating the technology timing outputs between devices for each lift. Therefore individual participant difference did not affect results. The final sample size was 90 timing durations between lifting peaks for inertial sensors located at C7 (30 skin, 30 vest, and 30 jacket samples) and 70 durations for inertial sensors located at T12 (35 skin and 35 vest samples). The same variable (time) was tested for agreement between two identical wearable devices during the same human movement pattern and located at the same anatomical location. The difference was that one of the two devices was sewn into a worn tight fitting garments and one was attached directly to the skin. These data yielded three separate agreements for comparison which included the agreement between timing outputs for inertial sensors located on the skin versus in the vest at C7, on the skin versus in the jacket at C7, and on the skin versus in the vest at T12. Due to the strong agreement with infrared 3D motion capture previously quantified [4], the skin mounted sensor data were used as the criterion measure.

The agreement was assessed via a Will Hopkins Typical Error of the Estimate validation and the relationship was determined with a Pearson's correlation. Will Hopkins statistical method assesses the concurrent validity of a practical variable compared to a criterion variable. The two variables are the same measure but typically performed with different methods. A practical variable is considered valid if the measure is significantly close (agreement) to the true values occurring [10]. The criterion is typically a gold standard measure or a variable that is as close to the true values of the measure as possible. Validity between the practical variable and criterion variable (agreement) is analysed by the standardised error, calculated by error (raw units) divided by the standard deviation of the criterion values predicted by the practical variable (evaluated via correlation coefficients to allow estimation of confidence limits). Standardised error results were interpreted using half the Will Hopkins modified Cohen scale: <0.10, trivial; 0.1–0.3, small; 0.3–0.6, moderate; 0.6–1.0, large; 1.0–2.0, very large >2.0 [10]. To further confirm validation, a Bland Altman Limits of Agreement was further completed to cross examine the raw error of estimate results with the Will Hopkins Typical Error of the Estimate validation [11].

3. Results

Validation results demonstrate the high agreement for accurately detecting the timing of resistance exercise movement patterns with inertial sensors embedded in clothing (Table 1). For all three differences analysed, the Will Hopkins standardised error of the estimate was trivial (<0.1) (0.038, 0.055, and 0.065 respectively). There was a strong agreement for mean difference results (0.000 s, 0.005 s, and 0.002 s respectively), and the Pearson's correlation coefficient was near perfect ($r = 0.999$, $r = 0.999$, and $r = 0.998$ respectively). Results remained consistent between statistical validation methods and 95% confidence limits were very narrow for all three validations.

4. Discussion

This research aimed to validate temporal outputs of inertial sensors located in tight fitting clothing and garments during human movement. Results demonstrated significant agreement, validating the mounting of inertial sensors at C7 and T12 in wearable vests and jackets (Table 1). Previous research reported timing outputs during resistance exercise from inertial sensors placed on the skin had trivial standardised error (0.026) and significant Pearson's correlation ($r = 0.9997$) when compared to 3D motion capture [4]. This previously validated relationship enabled inertial sensors placed on the skin to significantly reflect a higher standard (3D motion capture) of human movement monitoring and therefore be utilised as the criterion measure. Past research [4] made it possible to

analyse the use of wearable inertial sensors to monitor timing during resistance exercise, via measuring the agreement between sensors placed on the skin and sensors embedded in clothing. It was not possible to directly assess the agreement between wearable inertial sensors and 3D motion capture due to clothing blocking any skin mounted reflective markers. It was concluded that wearable inertial sensors mounted in tight fitting clothing can now be used with as much confidence as skin mounted sensors for monitoring timing of human movement during resistance exercise.

Table 1. Measures of validity.

	Estimate	Lower CL	Upper CL
C7 Skin vs. Vest			
Raw Error (s)	0.032	0.026	0.041
Standardised Error (Cohen scale)	0.038	0.031	0.048
Pearson Correlation (r)	0.999	0.999	1.000
Mean Difference (s)	0.000	-0.011	0.012
T12 Skin vs. Vest			
Raw Error (s)	0.048	0.040	0.060
Standardised Error (Cohen scale)	0.055	0.046	0.069
Pearson Correlation (r)	0.999	0.997	0.999
Mean Difference (s)	0.005	-0.011	0.022
C7 Skin vs. Jacket			
Raw Error (s)	0.054	0.045	0.070
Standardised Error (Cohen scale)	0.065	0.053	0.083
Pearson Correlation (r)	0.998	0.996	0.999
Mean Difference (s)	0.002	-0.018	0.022

Legend: C7 = Cervical vertebrae segment 7. CL = Confidence limit. *r* = Pearson correlation coefficient. s = Seconds. T12 = Thoracic vertebrae segment 12. vs. = Versus.

Agreement results for raw error (s) were combined in Table 1 to demonstrate the Bland Altman Limits of Agreement statistical analysis generating the same raw error result as the Will Hopkins Typical Error of the Estimate validation. The mean difference of timing durations from sensors embedded in clothing when validated with skin fixed sensors had strong agreement (very close to zero), evident from the very narrow confidence limits that included zero (Table 1). Therefore it is 95% confident that there is no statistically significant difference between group means for all three validations. This is further supported by the near perfect Pearson’s correlations for all three agreement tests [10]. The standardised error from Will Hopkins results were all trivial (<0.1), quantifying the close association between the practical and criterion variable. Therefore the practical methodology is now a valid method of monitoring anteroposterior (flexion and extension) movement of the C7 and T12 spinal landmarks during deadlifts with wearables. Due to the strength of results, it can be assumed that this validity may be translatable to similar resistance exercises and manual handling tasks, at typical device locations, and mounting in other varieties of clothing. Any movement that incurs skeletal muscle contraction to oppose an external resistance or force (such as gravity) can be considered as resistance exercise. Therefore, these results support any application incorporating temporal measures of human movement during any forms of resistance exercise, collected from wearable devices.

Magnitude measured from sensors fixed to skin has been previously validated for human joint motion tracking with trivial positional errors and angle errors of less than five degrees [12]. Compared to other methods, wearables may have significantly greater noise and improper alignment to anatomical axis due to the movement from poor fixation of devices [13]. These limitations may influence magnitude errors and increase as fixation decreases. By implementing wearables in tight fitting garments, any human error of manual attachment may be eliminated. In addition, when plotting magnitude and timing, relatively small errors in magnitude may not influence timing outputs. Specifically, changes in gyroscope data still happen at the exact time they occurred in real

time, regardless of magnitude [4]. Therefore, timing output from wearables may be utilised as a standalone means to derive important information. However, this research was performed in a controlled environment to ensure immunity of clothing artefact due to any environmental conditions. Therefore these results may not be translatable if wearables are implemented in analysis with environmental fluctuations present. Future research and technology advances in sensor fusion methods may further reduce these errors such as drift limitations or extreme environments.

The strength of these results is that wearables can now be confidently implemented to quantitatively monitor timing outputs of human movement. Multiple wearables may be simultaneously recording data during a task while accurately deriving and relaying important information in real time. Therefore this method of human movement monitoring has multiple potential practical applications across many societal areas. Timing data of human movement can be fused with other sensor outputs and incorporated into mainstream recreational exercise trackers for many purposes such as tracking the number of repetitions or the time taken to complete exercise sets. There may also be potential health or performance feedback applications to monitor injury risks or safe and efficient performance of a resistance exercise during strength training. Wearable sensors may also be applied as a judging tool in professional sports to assist judges, by quantitatively reporting timing measures. Furthermore, various applications for workplace settings include monitoring which segments of the body are moving, when they are moving, how long they are moving for and the number of repetitions performed during a specific task or for the duration of a working shift. These timing outputs of human movement may be applied to track the efficiency of staff members by monitoring the time taken to complete tasks or by tracking the number of items shifted. The safety of staff may be monitored by incorporating sensor data in injury risk factor estimations, monitoring falls, tracking fatigue, and work to rest ratio. With wearable sensors, these factors may be monitored for a single task or over a working shift, without impeding on work. Human movement data can be collected and linked to smartphone applications or computer programs with friendly user interface designs, which could provide feedback in real time or compile reports for review. The benefits of implementing wearable technology are the practicality of use in occupational environments, low cost, constant development and enhancement of technology, the accuracy of human movement measures, and the limitless potential for applications. Future interventions of wearable sensors in the workplace may lead to productivity increases or reducing workers compensation costs through increasing health and safety.

5. Conclusions

This novel validation demonstrated significant possibilities for future interventions utilising temporal parameters of wearables and was of importance for several reasons. Results fill a gap in the literature, with no known validation for temporal outputs of wearable inertial sensors existing, despite many interventions utilising sensors embedded in clothing. This research supports previous research and provides a foundation for future human movement applications implementing wearable inertial sensors. The strength of these results can now be referred to as a reference point to support the use of monitoring timing of human movement with wearables during other research interventions and practical applications. The process of validation for new technologies and methods applied in elite sport is pivotal before application can occur. The development and validation of technology that has permeated sport and exercise assesses fundamental human movements for health, safety and performance benefits. These fundamental components of human movement are translatable to numerous societal areas. What is called for now is the use of this validated information to develop quantitative human movement event detection interventions with wearables in environments where resistance exercise is common practice, such as occupational environments, recreational exercise, professional sport, rehabilitation, and activities of daily living.

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