Journal of Bodywork & Movement Therapies 23 (2019) 461–465

Contents lists available at ScienceDirect

Journal of Bodywork & Movement Therapies

journal homepage: www.elsevier.com/jbmt

Observational Study

Google fit smartphone application or Gt3X Actigraph: Which is better for detecting the stepping activity of individuals with stroke? A validity study

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A R T I C L E I N F O

Article history:
Received 26 January 2019
Accepted 27 January 2019

Keywords:
Hemiplegia
Validation
Cell phone
Accelerometry

A B S T R A C T

Objective: To examine the validity of the GT3X® ActiGraph accelerometer and the Google Fit® smartphone application in estimating stepping activity in people with chronic stroke.
Methods: Thirty-seven stroke survivors walked along a straight, 10 metre hallway over 5 min at their fastest speeds, wearing the GT3X® ActiGraph accelerometer and a smartphone on their paretic lower limb. The criterion-standard measurement made was the actual number of steps, counted by a trained examiner.
Results: The mean estimated steps measured by the GT3X® ActiGraph and Google Fit® respectively were 276.7 ± 97.6 and 481.0 ± 119.8; that calculated from the examiner's measurements was 472.0 ± 93.9. Statistically significant associations were found between the actual steps and those estimated by the GT3X® ActiGraph ($r = 0.56$; $p < 0.001$) and Google Fit® ($r = 0.89$; $p < 0.001$). The Google Fit® application demonstrated the highest reliability coefficient ($ICC[2,1] = 0.93$; $p < 0.001$; $p = 0.37$), compared to that of the GT3X® ActiGraph ($ICC[2,1] = 0.32$; $p < 0.001$; $p < 0.001$).
Conclusions: The GT3X® ActiGraph underestimated the data and may not be the most appropriate device to estimate the stepping activity of stroke patients. The findings support the validity of a smartphone application in estimating the stepping activity of individuals with stroke, when worn on the paretic side.

1. Introduction

The adoption of active lifestyles is of paramount importance for individuals with stroke, to prevent additional comorbidities and new stroke episodes (Billinger et al., 2014). However, the activity levels of stroke survivors tend to be lower than those observed for sedentary, healthy subjects (Tudor-Locke et al., 2011). In this sense, more active behaviors should be encouraged by assessing and monitoring the patients' levels of daily walking activities. One way to do this is by encouraging the use of stepping activity monitors as motivators to increase the total walking time and the amount of daily medium and long walking bouts (Danks et al., 2014).

The use of pedometers in step activity monitoring programs was found to be associated with significant increases in physical activity levels of individuals with chronic stroke (Bravata et al., 2007). Previous studies hypothesized that counting the number of steps should be considered the preferred method to assess and monitor levels of daily activity of stroke survivors (Pearson et al., 2004; Tryon, 1991), since step counts are considered natural units of walking activity (Tryon, 1991). In addition, step counting has been considered the gold-standard measure of mobility and walking activity for these individuals (Pearson et al., 2004). In support of this, there is a great variety of step monitors available on the market that allow people to keep track of their number of achieved daily steps.

Step monitors usually use accelerometry-based technology, which has been frequently employed to measure ambulatory activity after stroke (Mudge et al., 2007; Steins et al., 2014; Fini et al.,

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https://doi.org/10.1016/j.jbmt.2019.01.011
1360-8592/

2015). These devices are small, non-invasive, and have small microprocessors which work continuously (Mudge et al., 2007), allowing the users to have trustworthy information on their activity levels. The GT3X® ActiGraph is an example of a frequently used triaxial accelerometer which can objectively measure the number of steps taken over a period of time and has been used with various neurological conditions (Mattlage et al., 2015; Balantrapu et al., 2014; Tweedy and Trost, 2005). However, devices such as the GT3X® ActiGraph have mainly been used for research purposes, since they are relatively expensive and not easily incorporated within clinical settings.

In an attempt to solve these issues, consumer-based activity monitors have been developed to monitor activity parameters, such as the number of steps taken over a period of time, burnt calories, and walked distances (Lee, 2013). A promising and cost-effective method in this scenario is the use of smartphone applications, since these devices have built-in accelerometers, gyroscopes, and global positioning systems (GPS) (Google Developers, 2016), which allow the users to have real-time access to their data. In addition, the data provided by smartphone applications may be compared with those of other people on social media. Although the use of smartphone applications was validated for healthy young subjects (Lee, 2013; Case et al., 2015), there are no available data for individuals with neurological conditions, including those with stroke.

Therefore, the aim of the present study was to examine the validity of both a smartphone application (Google Fit®) and the GT3X®ActiGraph accelerometer in estimating stepping activity in people with stroke. The estimated steps provided by both devices were compared with the actual steps, which were counted by a trained examiner. This information may be useful to recommend these devices for monitoring stepping activity.

2. Methods

2.1. Participants

Individuals who had had a single unilateral stroke were recruited from the general community of a metropolitan city of Brazil by means of advertisements and by screening out-patient clinics in public hospitals from August 2015 to August 2016, according to the following criteria: They were older than 20 years; at least six months had elapsed since the onset of the stroke; they were able to walk independently with or without assistive devices; they had residual weakness or increased tonus of the knee extensor and/or ankle plantar flexor muscles; they showed no cognitive impairments, as determined by the following education-adjusted cut-off scores on the Mini Mental State Examination: 13 for the individuals with illiteracy and 18 for those with basic education (Bertolucci et al., 1994). Participants were excluded if they had any other non-stroke related conditions. All participants provided written consent, based upon previous approval from the Institutional Ethical Review Board (#CAAE−47256815.9.0000.5149).

The sample size was calculated a *posteriori* by the GPower 3.1 software, resulting in a power of 0.98.

2.2. Instruments and procedures

Initially, the participants underwent an interview and physical examination for the collection of their demographic, anthropometric, and clinical data, which included: age; sex; body mass; height; time since stroke onset; paretic side; cognitive assessment (Mini Mental State Examination); functional status evaluated by the 10-m walking test (10MWT); motor recovery of the lower limb as determined by the Fugl-Meyer lower-extremity section scores.

They were then asked to walk back and forth along a 10m, flat and straight hallway over 5 min at their maximum speeds, following previously recommended procedures (Polese et al., 2015), wearing the GT3X® ActiGraph accelerometer on their paretic ankle and carrying a smartphone in the front pockets of their paretic lower limb, following previously recommended procedures (Capela et al., 2015). A research assistant also videotaped the participants as they walked. The actual steps were determined by a trained physical therapist (PT), who counted the steps taken by the participants from the videotape recordings on two occasions, at least one week apart. This period of time was chosen to avoid memory bias. The PT had five years of research and clinical experience in the area of stroke rehabilitation. Excellent test-retest reliability (ICC [3.1] = 0.98; $p < 0.001$) was found. Then, the actual number of steps identified by the PT was used as a criterion-standard measure.

2.3. GT3X® ActiGraph accelerometer

The GT3X®ActiGraph is a small, commercially available, triaxial accelerometer which captures changes in acceleration in the anteroposterior, lateral, and vertical axes (Buonani et al., 2013) and predicts, amongst other variables, the number of steps taken over a period of time. It can be positioned on different body regions and, in the present study was placed on the paretic ankle as recommended by the manufacturer and previously employed by stroke survivors (Mattlage et al., 2015). This positioning was chosen due to the fact that accelerometers provide more reliable step count data in older adults with or without assistive devices when placed on the ankle versus the hip or spine (Korpan et al., 2015; Treacy et al., 2017). The collected data were analyzed by the ActiLife data analysis software 4.1.0.

2.4. Google Fit® smartphone application

The Google Fit® is an open platform developed by Google Inc., which allows the users to control their fitness data. It is also available as a free application for smartphones, which works with versions above 4.0 in Android systems. The Google Fit® consists of a set of high level sensors, such as an accelerometer, a gyroscope, and a GPS system which can detect changes in position (for example, moving from sitting to standing), various types of movement (walking, cycling, and others), several kinds of data (number of steps, walked distance, heart rate, and others), and different bouts of activity (time of each bout) (Google Developers, 2016). The smartphone used in the present study was the LG Nexus 5, which weighted 130 g and had the following dimensions: 69.17 mm width, 137.84 mm height, and 8.59 mm depth.

Prior to the test, the smartphone was positioned in the front pockets of the participants' paretic lower limb, as previously employed with stroke survivors (Capela et al., 2015) and calibrated according to the following participants' data: sex, body mass (Kg), and height (cm).

2.5. Statistical analyses

Descriptive statistics and tests for normality (Shapiro-Wilk) were carried out with the SPSS software (version 19.0) by an independent researcher. Pearson's correlation coefficients were calculated to examine the associations between the criterion-standard measure (actual steps) and those estimated by the Google Fit® application and the GT3X® ActiGraph accelerometer, considering the following cut-off values (Portney and Watkins, 2009): 0–0.25: little or none; 0.26–0.50: fair; 0.51–0.75: moderate to good; and >0.75: good to excellent relationship. Intra-class correlation coefficients (ICC [2,1]) were calculated to investigate the relative reliability between the actual steps and those estimated by the Google Fit application and the GT3X® ActiGraph accelerometer. The significance level was set at 5%.

3. Results

3.1. Participants' characteristics

Initially 38 individuals volunteered to participate, but one was excluded due to Parkinson's disease. A total of 37 individuals participated in the present study (28 men and 9 women) with a mean age of 62 ± 11 years and a mean time since the stroke onset of 91 ± 91 months. The participants showed high variability in functional levels, since their walking speed ranged from 0.3 to 1.4 m/s. Their characteristics are reported in Table 1.

3.2. Concurrent validity

The mean (SD) number of the steps estimated by the Google Fit® application and the GT3X® ActiGraph accelerometer was 481.0 ± 119.6 and 276.7 ± 98.8 respectively, whereas the mean actual number of steps counted by the examiner was 472.0 ± 93.0. Significant and positive associations were found between the actual steps and those estimated by the Google Fit application ($r = 0.89$; $p < 0.001$) and the GT3X® ActiGraph accelerometer ($r = 0.56$; $p < 0.001$).

The ICC (2,1) analyses revealed that data estimated by the Google Fit® application showed higher agreement (ICC = 0.93; $p < 0.001$; 95%CI = 0.86 to 0.96) and lower mean difference when compared with the actual stepping count (−8.3steps; $p = 0.37$), whereas the data estimated by the GT3X® ActiGraph accelerometer showed lower agreement (ICC = 0.32; $p < 0.001$; 95%CI = 0.16 to 0.67) and higher mean difference (191.8 steps; $p < 0.001$) (Table 2).

4. Discussion

This study aimed to examine the validity of a smartphone application (Google Fit®) and the GT3X® ActiGraph accelerometer in detecting stepping activity in individuals with chronic stroke, by comparing the data estimated by these devices with that determined by the examiner. The results showed that step activity estimated by the Google Fit® application was similar and highly associated with that counted by the examiner. However, the step count estimated by the GT3X® ActiGraph was lower and showed moderate association with that determined by the examiner. The ICC (2,1) revealed that the data estimated by the Google Fit® application showed better agreement and lower relative bias than that estimated by the GT3X® ActiGraph when compared with the actual steps.

Corroborating the present findings, a previous study examining the accuracy of the AM7164®ActiGraph accelerometer in estimating the number of steps in individuals with multiple sclerosis also found that the accelerometer showed a tendency to underestimate the number of steps during walking, mainly when walking speed was lower than 0.9 m/s (Motl et al., 2011). Although the version of the ActiGraph accelerometer used in the present study was more recent, the results were similar and could be partially explained by the mean walking speed of the participants, which was similar to the study of Motl et al. (2011). A possible reason for this may be that regular accelerometers usually do not consider gait asymmetries, which are typical features of individuals with stroke (Kerrigan et al., 2000; Stanhope et al., 2014). It is important to notice that the algorithms used to estimate the data from ActiGraph accelerometers are based upon studies with healthy individuals (Freedson et al., 1998), who usually do not have any marked gait asymmetries. However, previous studies found that ActiGraph accelerometers can also underestimate step counts of healthy middle-aged adults (Motl et al., 2011) and the community-dwelling elderly (Paul et al., 2015). In addition, the results of a recent study showed that the GT3X®ActiGraph accelerometer data also showed poor agreement with the observed step counts when individuals who walked at slow speeds were evaluated in an inpatient rehabilitation setting (ICC [2,1] = 0.123–0.399) (Treacy et al., 2017).

Another important point is that even though there are different triaxial accelerometers available from ActiGraph, the algorithms used by the manufacturer were developed by taking into account only the vertical axis data (Freedson et al., 1998). Compared to movements in the frontal and sagittal planes, joint range of motion in the transverse plane, i.e., internal and external rotations, is more limited, even in healthy individuals. Thus, the vertical axis would probably not be the best sources for estimating the stepping activity of individuals with stroke. In this sense, data from the other

Table 1
Characteristics' of the participants.

Characteristic	$n = 37$
Age (years), mean ± SD, (range: min–max)	62 ± 11 (24–82)
Sex (men), n	28
Body mass (kg), mean ± SD (range: min–max)	74.5 ± 14.9 (50–117)
Height (cm), mean ± SD (range: min–max)	164.7 ± 8.6 (142–184)
Time since stroke (months), mean ± SD, (range:min–max)	91 ± 91 (9–412)
Side of paresis (left), n	19
MMSE (scores 0–30), mean ± SD	25.6 ± 4.9
Fugl-Meyer lower limb section (scores 0–34), mean ± SD	20.3 ± 5.8
Gait speed (m/s), mean ± SD, (range: min-max)	
Comfortable	0.9 ± 0.3 (0.3–1.4)
Fast	1.3 ± 0.6 (0.5–2.1)
Walking distance, mean ± SD	294.1 ± 156.7
Estimated steps by the GT3X® ActiGraph (number), mean ± SD	276.7 ± 98.8
Estimated steps by the Google Fit application (number), mean ± SD	481.0 ± 119.6
Actual steps counted by the examiner (number), mean ± SD	472.0 ± 93.0

Activity Monitor	ICC (2,1) (95% CI)	Mean difference between activity monitor estimated steps and actual steps (95CI)
Actigraph GTX3	0.385 (−0.227 to 0.720)	387.5 (322.6–452.3)
Google FIt	0.914 (0.818–0.959)	454.6 (452.2–457.0)

MMSE = Mini-mental state examination; SD= Standard deviation.

Table 2
Intra-class correlation coefficients and 95% confidence intervals between the actual steps and those estimated by the Google Fit application and the GT3X Actigraph accelerometer ($n = 37$).

Device	ICC [2, 1] (95%CI)	Mean difference (95%CI) between the actual and the estimated steps
Google Fit application	0.93 (0.86–0.96)	−8.29 (−26.76 to 10.18)
GT3X Actigraph accelerometer	0.32 (−0.18 to 0.68)	191.82 (160.79–222.84)

axes, mainly from the anterior-posterior axis would probably be the best components to consider, since to advance their paretic limb, stroke survivors usually tend to abduct it to perform a circumduction (Kerrigan et al., 2000; Stanhope et al., 2014).

There are different activity monitors currently commercially available, such as the Fitbit Ultra, Fitbit One, and Nike Fuel+, which have been used for estimating stepping activity of stroke patients (Fulk et al., 2014; Klassen et al., 2016). However, all of them have shown some limitations. For instance, although the number of steps estimated by the Fitbit Ultra showed good association with those obtained by video recordings (ICC = 0.70) (Fulk et al., 2014), a tendency to underestimate of the data for individuals with gait speeds lower than 0.58 m/s was found (Fulk et al., 2014). The Fitbit One also showed considerably higher mean errors in estimating stepping activity (15.8%) in individuals with chronic stroke who walked at lower speeds (Klassen et al., 2016). Finally, the data estimated by the Nike Fuel + showed the lowest associations with that determined by observation of stroke survivors ($r = 0.19$) (Fulk et al., 2014). Corroborating previous findings, the participants of the present study also included slow walkers, walking with speeds ranging from 0.3 to 1.4 m/s.

Smartphone applications were found to provide accurate measurements of stepping activity in healthy young subjects and to the best of our knowledge, this is the first study which investigated its validity with individuals with chronic stroke. The results supported the use of the Google Fit® smartphone application as a good alternative to estimate the stepping activity of these patients, since its data showed higher associations with that determined by the examiner than the data estimated by the GT3X® ActiGraph accelerometer. It is important to note that it might be difficult for some patients to access some consumer-based activity monitors because they could be relatively expensive. On the other hand, the Google Fit® application is an open platform which is freely available for mobile phones, making it more accessible to people to keep track of their walking activity. Thus, the findings that the Google Fit® application provides valid measures of stepping activity may have important clinical implications. This would allow rehabilitation professionals and patients to monitor the amount of step activity over a period of time and stimulate patients to have more active and healthier life styles. In contrast to other consumer-based activity monitors, the Google Fit® application does not require a computer to process the information since it provides instantaneous data using an easy-to-read interface, and therefore, it is more practical and less time-consuming if employed within clinical environments. Lastly, the users would have no additional financial expenses, considering that more than 62% of the worldwide population already have a mobile telephone (Statistica, 2017).

Although participants in the present study displayed a wide range of walking speeds, it is important to note that they were in the chronic stages of stroke and walked in a closed environment. Therefore, the results should not be extrapolated for individuals with different characteristics and in different conditions. Future studies should examine other measurement properties of smartphone applications and different types of telephones in individuals with other characteristics and in different environments.

5. Conclusion

The findings of the present study support the validity of the Google Fit® smartphone application in estimating stepping activity of individuals with chronic stroke during fast overground walking. In addition, its cost-effectiveness makes it an interesting alternative to be incorporated within clinical contexts. The GT3X® ActiGraph accelerometer tended to underestimate the data and did not appear valid for estimating stepping activity in individuals with chronic stroke.

Support

This research was supported by the following Brazilian national grant agencies: CAPES (code #001), CNPq (#304430/2014-0), and FAPEMIG (PPM-00082-16).

Conflicts of interest

None.

Acknowledgment

The authors would like to acknowledge the staff members of the “Laboratório de Avaliação e Pesquisa em Desempenho Cardiorrespiratório” (LabCare) for their technical support.

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