DEPARTAMENTO DE CIENCIAS BIOMÉDICAS

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TESIS INTERNACIONAL POR COMPENDIO DE PUBLICACIONES

VALIDACIÓN DEL ACELERÓMETRO ACTIGRAPH GT3X PARA LA CUANTIFICACIÓN DE LA ACTIVIDAD FÍSICA

"VALIDATION OF THE ACTIGRAPH GT3X ACCELEROMETER TO QUANTIFY PHYSICAL ACTIVITY"

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A mi familia, por todo su amor

"Dream as if you'll live forever. Live as if you'll die today"

Quote by James Dean

“All the world is made of faith, and trust, and pixie dust”

Quote by J.M. Barrie in Peter Pan

"Not all treasure is silver and gold, mate"

Quote by Johnny Depp as Captain Jack Sparrow

“Las dunas cambian con el viento, pero el desierto sigue siendo el mismo”

Pablo Coelho en “El Alquimista”

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TESIS POR COMPENDIO DE PUBLICACIONES

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Paper IV: Santos-Lozano A, Garatachea N. *Tendencias actuales de la acelerometría para la cuantificación de la actividad física*. *Current trends of accelerometry to assess physical activity*. RICCAFD. 2012 Ago; 1 (1): 24-32.
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Resumen

Debido al elevado interés por evaluar los niveles y la naturaleza de la actividad física en distintos grupos de edad, y al importante desarrollo tecnológico en los últimos años, se han desarrollado nuevos instrumentos para medir el nivel de actividad física de forma objetiva, destacando entre ellos los acelerómetros.

Conocer tanto la fiabilidad intra e inter monitor como su validez, no solo facilita a los investigadores una información crítica para la elección de un modelo u otro de acelerómetro, si no que también permite controlar la calidad y la objetividad de los resultados proporcionados por los acelerómetros. En 2009, ActiGraph lanzó al mercado un nuevo modelo triaxial denominado GT3X.

El objetivo principal de los trabajos realizados es validar el acelerómetro Actigraph GT3X para la cuantificación de la actividad física. Para ello se realizaron tres fases experimentales: fase I, fiabilidad mecánica; fase II, fiabilidad durante actividades físicas estandarizadas; y fase III, evaluación de la precisión de ecuaciones conocidas y calibración del modelo de acelerómetro en distintos grupos de edad.

Los principales resultados de la memoria de tesis sugieren que:

- El acelerómetro GT3X puede ser útil para evaluar el nivel de actividad física en humanos según la validación mecánica realizada.
- Bajo condiciones estandarizadas se encontró una fiabilidad inter-instrumento del acelerómetro GT3X en todos los planos.
- La localización del monitor puede modificar el registro del mismo.
- Las nuevas ecuaciones aquí propuestas aportan una estimación de gasto calórico mucho más precisa para cada uno de los grupos de edad que las publicadas previamente.
- Los nuevos cut-points específicos propuestos para cada grupo de edad proporcionan una herramienta útil para determinar los niveles de actividad física con el acelerómetro GT3X.

Los resultados muestran que el acelerómetro GT3X parece ser una herramienta útil para estimar gasto calórico y puede ser lo suficientemente sensible para diferenciar entre niveles de actividad física. Al menos en condiciones de laboratorio.

Summary

Due to the high interest to evaluate the physical activity nature and levels of different population groups, and also the important technological development in recent years, new tools have been developed to measure the level of physical activity objectively, among them the accelerometers highlight.

Knowing both intra-and inter-monitor reliability as well as validity, not only provides to the investigators a critical information for choosing one model or another accelerometer, but rather also it possible to control the quality and objectivity of the results provided by the accelerometers. In 2009, ActiGraph launched a new model called triaxial GT3X.

The aim of our work is to validate the accelerometer Actigraph GT3X quantifying physical activity. This was carry out three experimental phases: Phase I: mechanical validation, phase II: validation under standardized physical activities and phase III: evaluation of the accuracy of previously published equations and to calibrate the accelerometer model in different population groups.

The main results of the PhD dissertation suggest that:

- The mechanical validation provides support for the use of this instrument in studies to assess the level of physical activity in humans.
- Under standardized conditions it was found an internal reliability GT3X accelerometer instrument at all levels.
- The location of the accelerometer could influence on the accelerometer out-put.
- The new proposed equations here provide more accurate energy expenditure prediction than other previously published for each of the groups.
- The new GT3X cut-points given for each specific age group provide a useful tool determining physical activity levels.

The results show that the accelerometer GT3X seems to be a useful tool estimating energy expenditure and may be sensitive enough differentiating between physical activity levels, at least under standardized conditions.

1. Introducción

1.1 Importancia de cuantificar niveles de actividad física.

Desde que las guías de salud publicadas por las autoridades sanitarias recomiendan desarrollar actividad física de manera regular, se ha elevado el interés por evaluar los niveles de actividad física y su naturaleza en distintos grupos poblacionales (1, 2). En 1985 Caspersen et al. (3) definieron la actividad física como cualquier movimiento corporal producido por los músculos esqueléticos y que requiere un cierto gasto energético. La unidad metabólica es el MET, definiéndose 1 MET como el consumo de oxígeno [VO_2] en reposo, que aproximadamente equivale a 3.5 $ml\cdot kg^{-1}\cdot min^{-1}$. En función de las unidades metabólicas, la intensidad de la actividad física se puede clasificar en: ligera (<3.00 METs), moderada (3.00-5.99 METs), vigorosa (6.00-8.99 METs) y muy vigorosa (≥9 METs) (4, 5). La necesidad de comprender mejor la relación entre el nivel de actividad física y diferentes indicadores de salud, así como poder explicar el drástico aumento en la prevalencia de sobrepeso y obesidad en la población, ha llevado a los investigadores a mejorar las herramientas utilizadas para cuantificar los niveles de actividad física (6).

1.2 Cuantificación objetiva de actividad física

El importante desarrollo tecnológico en los últimos años ha permitido desarrollar nuevos instrumentos para medir el nivel de actividad física de forma objetiva, como por ejemplo los podómetros y acelerómetros. Los podómetros, mediante un sencillo sistema pendular ya ideado por Leonardo Da Vinci, miden el número de pasos que se realizan en un determinado periodo de tiempo, aunque no da información de la intensidad de la actividad física (7). En los últimos años se ha incrementado la popularidad de los acelerómetros como herramientas de cuantificación objetiva de la actividad física en distintas poblaciones (8-10) ya que supera los inconvenientes de los podómetros. Así, los acelerómetros se han convertido en uno de los métodos más utilizados actualmente debido a la información que proporcionan sobre intensidad, frecuencia y duración de la actividad física (11, 12).

1.2.1. Acelerómetros

Los acelerómetros registran el cambio de aceleración del centro de masas en diferentes ejes o planos de movimiento y la convierten en una señal digital cuantificable denominada *counts*. Dependiendo del número de ejes en los que registran la información existen acelerómetros uniaxiales (un eje), biaxiales (dos ejes) o triaxiales (tres ejes). Actualmente coexisten en el mercado un amplio número de marcas y modelos de acelerómetros, pero ActiGraph (Pensacola, FL) es una de las más utilizadas por los investigadores para cuantificar el nivel de actividad física (10).

Figura1. Acelerómetro ActiGraph GT3X

En 2009, ActiGraph lanzó al mercado un nuevo modelo de acelerómetro denominado GT3X. Este modelo es un acelerómetro triaxial, que registra aceleración en los tres planos del espacio (eje Y, eje X y eje Z). La señal bruta en unidades de aceleración Gs es obtenida de la siguiente manera: 2.022 V (voltaje de la señal) – 1.5 V (0g compensación) / 174 $mV·g^{-1}$ (sensibilidad del acelerómetro). Posteriormente la señal es transformada rectificada y traducida a *counts* (13). Los *counts* son unidades de movimiento, normalmente, las marcas comerciales no proporcionan información para transformarlos en Gs, haciendo muy difícil la comparación de resultados entre modelos (6). Cada registro de *counts* es sumado y guardado en la memoria del acelerómetro en un intervalo de tiempo configurable denominado "*epoch*". De esta manera se define cada cuanto tiempo se graba un nuevo registro de aceleración. El *epoch* representa una medida cuantitativa de la actividad física en un cierto plazo de tiempo. La duración del *epoch* determina la resolución con la que la que se registraran los datos; cuanto más corto sea el *epoch* mayor detalle del registro existirá. Sin embargo, *epoch* más bajos no aumentan la exactitud de los datos recogidos (14). El investigador decide el periodo de tiempo o *epoch* en el que periódicamente se guardarán los datos: cada 1s, 5s, 15s, 30s o 60s habitualmente. Los *counts* obtenidos en un determinado *epoch* son proporcionales a la intensidad de la actividad física durante dicho período.

1.2.3 Fases de validación de un acelerómetro

Para seguir el desarrollo de esta memoria de tesis doctoral, es importante definir y diferenciar entre los conceptos de validez, fiabilidad y calibración (15).

- Validez: se refiere a la capacidad de un instrumento para medir con precisión el rasgo para cuya medición ha sido diseñado.
- Fiabilidad: hace mención a la tendencia que tiene un instrumento de medida a ser consistente durante medidas repetidas del mismo fenómeno. Cuanto más consistente sea tendrá mayor fiabilidad.
- Calibración: es una comparación entre instrumentos de medida, en el cual se conoce el valor real de la medición o se utiliza uno de ellos como estándar para mejorar la precisión de medida del otro.

Por tanto, mientras que la validez se centra en una propiedad particular de indicadores empíricos, la fiabilidad concierne la relación entre el concepto y el indicador. Y, la calibración es el proceso de mejora de la precisión de un instrumento (15).

Evaluar la fiabilidad de cada modelo de acelerómetro es muy importante puesto que es un requisito previo a su validez (16). Tal como Esliger et al. (17) describieron, "la calidad de la información proveniente de un acelerómetro es solamente tan buena como el monitor que la proporciona". Conocer tanto la fiabilidad intra e inter monitor como su validez, no solo facilita a los investigadores una información valiosa para la elección de un modelo u otro de acelerómetro, si no que también permite controlar la calidad y la objetividad de los resultados proporcionados por los acelerómetros (17-19). Cuanto más preciso sea la herramienta de medición del nivel de actividad física: (1) mejor se podrá conocer la relación entre actividad física y salud, cuantificar de manera más minuciosa la eficacia de una estrategia de intervención para modificar estilos de vida y estimar de modo más exacto los niveles de actividad física de distintas poblaciones (20).

Fase I: fiabilidad mecánica

La primera fase para evaluar la fiabilidad de un acelerómetro es someterlo a una aceleración generada por un dispositivo mecánico. El uso de un dispositivo oscilatorio para evaluar la fiabilidad de los acelerómetros, de manera previa a estudios con humanos y actividades físicas de la vida diaria, ofrece ventajas metodológicas importantes (17) : i) los acelerómetros pueden ser expuestos a una gran variedad de aceleraciones, ii) existe la posibilidad de que varios acelerómetros registren datos de manera simultánea bajo las mismas condiciones, y iii) se puede tener un gran control en la reproductibilidad de las oscilaciones entre sesiones. Por ello, es importante que el primer paso para la validación del acelerómetro GT3X se hiciera en condiciones mecánicas controladas. Aunque hay estudios de fiabilidad intra e inter monitor de distintas generaciones de modelos de acelerómetros ActiGraph (17, 21-24), la fiabilidad del ActiGraph GT3X no se había estudiado anteriormente.

Fase II: fiabilidad durante actividades físicas estandarizadas

A pesar de las ventajas mencionadas anteriormente, evaluar el funcionamiento de los acelerómetros en condiciones mecánicas controladas no proporciona una evaluación real de su comportamiento durante la realización de actividades físicas diarias (25) donde se considera la variabilidad biológica. Por ello, la segunda fase de estudio es evaluar su fiabilidad mientras una persona lleva el monitor. La utilización de actividades físicas bajo condiciones controladas de laboratorio ha sido anteriormente empleada con éxito para evaluar la fiabilidad y la variabilidad inter-monitor de otros modelos de acelerómetros (26). Así pues, consideramos que el segundo paso para validar el acelerómetro ActiGraph GT3X debía ser evaluar su fiabilidad inter-monitor durante actividades físicas estandarizadas en laboratorio.

Fase III: evaluación de la precisión de ecuaciones conocidas y calibración del modelo de acelerómetro en distintos grupos de edad

Además de evaluar la fiabilidad de los acelerómetros (16), también es muy importante conocer la precisión de estos acelerómetros a la hora de determinar el gasto calórico. Para ello se utilizan como referencia métodos *gold standard* como agua doblemente marcada o calorimetría directa o indirecta (6). La calorimetría indirecta se ha utilizado para validar numerosos modelos como el CSA ó 7164, el GT1M, el Tritrac, el Caltrac o el Kenz Select (27-34). En el manual de cada acelerómetro, así como en otros estudios independientes de calibración, se determinan ecuaciones matemáticas para estimar gasto calórico (METs o Kcal·min^{-1}) a partir de los *counts* registrados por el acelerómetro. Bassett et al. en 2011 (35) ponen de manifiesto que al realizar la validación de un acelerómetro no se valida el acelerómetro *per se*, siendo necesario que la validación del mismo está relacionado con el proposito para en cual se va a utilizar. Un acelerómetro puede proporcionar una información válida para un grupo de edad pero no para otro, por ello es aconsejable que las ecuaciones de estimación de gasto calórico sean específicas para cada grupo de edad (35). En el manual de ActiGraph se incluyen ecuaciones matemáticas de estimación para su utilización con el acelerómetro GT3X, sin embargo estas no son específicas para distintos grupos de edad (14). En la literatura existen estudios independientes que proponen ecuaciones para la estimación de gasto calórico en niños, adultos y mayores para otros modelos de acelerómetros (33, 36-40) pero no para el GT3X. Sasaki et al. (41), en 2011, fueron los primeros autores que desarrollaron un estudio independiente para comparar los *counts* registrados por el acelerómetro GT3X y el GT1M durante la realización de actividades estandarizadas en laboratorio. Su población fue de jóvenes adultos (26.9 ± 7.7 años) y concluyeron que únicamente los *counts* registrados por el eje Y de ambos acelerómetros son similares. Además, determinaron una ecuación matemática utilizando los *counts* del VM para estimar METs (METs=0.000863(VM)+0.668876; R^2=0.78, EEE=±1.3 METs).

La utilización de un *gold-estándar*, en este caso calorimetría indirecta, permite conocer la exactitud del acelerómetro estimando gasto calórico y también desarrollar nuevos modelos matemáticos para predecir el gasto calórico a partir de los *counts* (14, 37).

Además de todo lo anteriormente expuesto, se pueden definir también cut-points o puntos de corte para los valores de *counts* proporcionados por los acelerómetros (10, 42-44). Los cut-points son un método para evaluar y clasificar los niveles de actividad física. Se utilizan para relacionar un rango de valor de *counts* con unidades metabólicas. Hay que tener en cuenta que los valores de corte varían dependiendo de la marca, el modelo del acelerómetro y el rango de edad de la población que utilice el monitor (31, 38, 45-49). Debido a la importancia que tienen los niveles de actividad física en estudios epidemiológicos es necesario desarrollar unos valores de corte para cada modelo y grupo de edad (10).

2. Objetivos

- General
  - Validar el acelerómetro Actigraph GT3X para la cuantificación de la actividad física.

- Específicos
  - Examinar la fiabilidad intra e inter monitor del acelerómetro GT3X en todos sus ejes bajo cinco frecuencias de movimiento utilizando una plataforma vibratoria vertical. (Anexo I. Artículo titulado: “Technical variability of the GT3X”).
  - Estudiar la fiabilidad y la variabilidad inter-monitor del acelerómetro GT3X en todo sus ejes y en diferentes condiciones de actividad física estandarizadas en laboratorio. (Anexo II. Artículo titulado: “Intermonitor variability of the GT3X”).
  - Comparar el gasto calórico estimado utilizando las distintas ecuaciones publicadas para el acelerómetro

GT3X con el medido mediante calorimetría indirecta en jóvenes, adultos y personas mayores durante diferentes condiciones de actividad física estandarizadas. (Anexo III. Artículo titulado: "The Actigraph GT3X Accelerometer: validation and determination of physical intensity cut points across age-groups").

- Mejorar la precisión de la estimación del gasto calórico utilizando el acelerómetro GT3X en jóvenes, adultos y personas mayores. (Anexo III. Artículo titulado: "The Actigraph GT3X Accelerometer: validation and determination of physical intensity cut points across age-groups").

- Definir unos cut-points específicos para cada grupo de edad utilizando los counts del VM del acelerómetro GT3X. (Anexo III. Artículo titulado: "The Actigraph GT3X Accelerometer: validation and determination of physical intensity cut points across age-groups").

3. Material y método

3.1. Material

3.1.1. Acelerómetro GT3X

Este acelerómetro es ligero (27 g), compacto (3.8 x 3.7 x 1.8 cm) y posee una batería recargable de polímero de litio (14). El fabricante recomienda colocarlo a nivel de la cintura utilizando un cinturón elástico o un clip. Está construido a partir de un sensor triaxial de estado sólido que recoge información en tres ejes: vertical (eje Y), horizontal izquierda-derecha (eje X) y horizontal adelante-atrás (eje Z). Además, a partir de los datos anteriores se puede obtener el vector magnitud ($VM = \sqrt{X^2 + Y^2 + Z^2}$). El GT3X registra y mide variaciones de aceleración en un rango entre ~0.95 y 2.5 Gs (14). La salida de los datos del acelerómetro está digitalizada por un convertidor de analógico a digital (ADC) de 12 bits a razón de 30 Hz (14). Una vez digitalizada, la señal pasa a través de un filtro digital que limita la frecuencia a un rango comprendido entre 0.25 y 2.5 Hz (14). El acelerómetro GT3X permite su programación en *epochs* de 1, 5, 10, 15, 20, 30 y 60 segundos, incluyendo también la posibilidad de registrar los datos en bruto (RAW) sin necesidad de determinar previamente los períodos de muestreo. El registro de los datos en bruto ofrece la ventaja de poder modificar la duración del *epoch* posteriormente (14).

3.1.2. Plataforma vibratoria

Se utilizó una plataforma vibratoria de movimiento vertical impulsada por un motor trifásico (tipo JL 712-2) programado por un convertidor de frecuencia compacto (FRN0.75c1s, FRENIC-Mini Series; Fuji Electric, Japón) (figura 2).

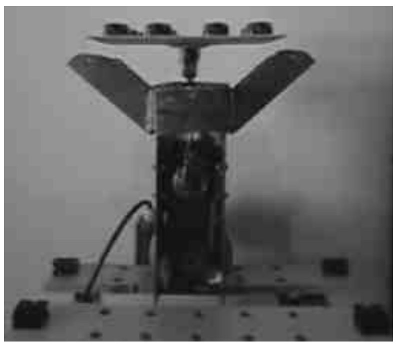

Figura 2. Plataforma vibratoria

El motor trifásico puede programarse con una frecuencia de movimiento dentro de un rango de 66-612 rpm (1.1-10.2 Hz). Esto proporciona una razonable simulación de un movimiento cíclico humano, como por ejemplo la marcha (24, 50).

3.1.3. Calorimetría indirecta

El gasto energético se midió mediante ergoespirometría de circuito abierto usando un sistema de medición metabólico Oxycon Pro, Jaeger-Viasys Healthcare (Hoechberg, Alemania) que permite una medición de gases respiración a respiración. El analizador de gases se calibró utilizando un gas con una mezcla conocida (16%O_2 y 5%CO_2) y un test de volumen antes de realizar la medición a cada sujeto (51).

3.1.4. Tapices rodantes

Un tapiz rodante Powerjog, modelo JM200 (Sport Engineering Ltd., GRB) y uno Quasar Med 4.0 h/p/cosmos (Nussdorf-Traunstein, Alemania) fueron necesarios para desarrollar las fases experimentales II y III respectivamente en las que se realizaba actividad física como caminar/correr a diferentes velocidades. Ambos dispositivos permiten aumentar la velocidad hasta los 25 km·h^{-1}.

3.1.5. Impedancia bioeléctrica

La composición corporal de los sujetos se evaluó mediante impedancia bioeléctrica utilizando un monitor de análisis de composición corporal (Tanita BC 420SMA Portable Body Composition Monitor).

3.2. Protocolos de las fases experimentales

Todas las fases experimentales estuvieron definidas y desarrolladas de acuerdo con la Declaración de Helsinki para la Investigación con Humanos en 1974 y cuya última modificación fue en 2008. También se tuvieron en cuenta los Estándares Éticos en Investigación en Ciencias del Deporte y del Ejercicio (52). Previamente a la realización de la fase II y III todos los sujetos firmaron un consentimiento informado escrito.

3.2.1. Protocolo fase I: Validación mecánica del acelerómetro GT3X

Se seleccionaron aleatoriamente 10 unidades del acelerómetro GT3X de entre 50 totalmente nuevas. Las 10 unidades GT3X se inicializaron y se programaron de forma sincronizada a través de un ordenador (*epoch* de 60 s). Una vez programadas e inicializadas, las unidades fueron colocadas en la plataforma de movimiento vertical de modo que la vibración solo se registrara en un eje (figura 3).

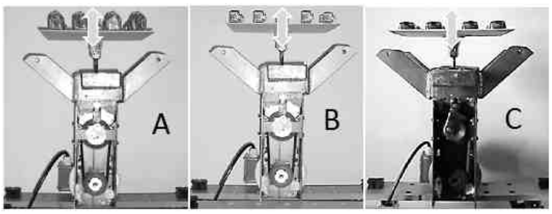

Figura 3. Colocación de los acelerómetros GT3X en la plataforma vibratoria. La flecha indica la dirección del movimiento. A) movimiento en el eje Y, B) movimiento en el eje X, C) movimiento en el eje Z.

Un investigador comprobó que cada unidad estuviera situada de manera segura en la plataforma vibratoria para evitar que se produjeran movimientos indeseados o desalineaciones de los monitores durante la vibración.

Los 10 monitores fueron expuestos a cinco condiciones de aceleración distintas (tabla 1) en cada uno de sus ejes (Eje Y figura 2A, eje X 2B y eje Z 2C). La amplitud fue constante en cada una de ellas (40 mm) modificándose únicamente sus frecuencias (1.1, 2.1, 3.1 4.1 y 10.2 Hz). Estas frecuencias se seleccionaron para proporcionar unos valores de *counts* relevantes dentro de un rango fisiológicamente humano, desde actividades clasificadas de intensidad ligera hasta de intensidad vigorosa (53). Las condiciones de aceleración se administraron de manera aleatoria y cada una de ellas fue mantenida durante 7 minutos. Previamente a iniciarse el registro, los monitores fueron expuestos a cada una de las condiciones durante 5 minutos como calentamiento (54).

Tabla 1. Descripción de las cinco condiciones de movimiento utilizadas

Condición	Frecuencia (Hz)	Aceleración (Gs)
1	1.1	1.083
2	2.1	1.087
3	3.1	1.093
4	4.1	1.164
5	10.2	4.143

Análisis estadísticos

Todos los análisis estadísticos se realizaron con el programa PASW (Predictive Analysis Software, v. 18.0, SPSS Inc., Chicago, IL, EE.UU.).

De los 7 minutos registrados en cada condición de aceleración se desecharon del análisis el primer y último minuto, por tanto fueron analizados los 5 minutos centrales de cada una de ellas.
Para determinar el efecto de la interacción de la frecuencia (1.1, 2.1, 3.1, 4.1 y 10.2 Hz) y del eje (Y, X y Z), se utilizó una ANOVA de medidas repetidas de dos vías (eje X frecuencia). En el caso de existir resultados significativos, se utilizó como test poc-hoc el test de Bonferroni para la comparación de los mismos por pares.

Para la evaluación de la fiabilidad intra-instrumento, se calculó el coeficiente de variación intra-instrumento (CVintra) de cada monitor para cada uno de los 5 minutos analizados en cada condición (CV = desviación estándar / media). Esta variabilidad "minuto a minuto" identifica la habilidad del acelerómetro para registrar con precisión las aceleraciones durante las condiciones proporcionadas por la plataforma vibratoria.

Para evaluar la fiabilidad inter-instrumento se utilizó el coeficiente de correlación intraclase (ICC). Se realizó este análisis para determinar la relación entre monitores utilizando los tres ejes combinados y los ejes de forma independiente. Un valor de ICC próximo a 1 representa una buena repetitividad (55). Por último, se calculó el coeficiente de variación inter-instrumento (CVinter) para cada eje en cada frecuencia.

3.2.2. Protocolo fase II: Validación del acelerómetro GT3X durante actividades físicas estandarizadas

La fiabilidad y la variabilidad intermonitor del acelerómetro GT3X fue evaluada bajo 6 condiciones (56): (i) reposo (sentado en un silla), (ii) caminar a 4 km·h^{-1}, (iii) caminar a 6 km·h^{-1}, (iv) correr a 8 km·h^{-1}, (v) correr a 10 km·h^{-1} y (vi) levantarse y sentarse de una silla de forma continua manteniendo una cadencia de 40 repeticiones por minuto. Todas las actividades se desarrollaron en una tapiz rodante (Powerjog, modelo JM200, Sport Engineering Ltd., GRB) y la condición de sentarse y levantarse de una silla también colocando una silla encima del tapiz detenido. Cada condición se mantuvo durante 12 min, con un descanso de al menos 10 min entre cada una de ellas.

Se seleccionaron aleatoriamente 8 monitores del acelerómetro GT3x de una muestra de 50 que tenían un mes de vida. Los 8 monitores fueron evaluados simultáneamente en el mismo sujeto (hombre sano y sin ningún tipo de desequilibrio en la marcha, 27 años de edad, 181.0 cm de altura y peso 76.5 kg). Los monitores fueron programados e inicializados de forma sincronizada a través del programa Actilife 4.0. (*epoch* de 60 s). Los 8 acelerómetros se colocaron en 2 bloques de 4 unidades firmemente anclados uno junto al otro y con la misma orientación (26). Estos 2 bloques se fijaron de forma segura un cinturón elástico y se colocó un bloque sobre la cadera izquierda y otro sobre la cadera derecha del sujeto. Al inicio y al final de cada condición, un investigador comprobó la correcta localización de cada bloque.

Análisis estadísticos

El primer y el último minuto de cada condición fue eliminado para el análisis estadístico, por lo que se analizaron los 10 minutos centrales de cada condición.

Para examinar la fiabilidad y la variabilidad intermonitor de cada condición, se calculó el ICC, CV y el intervalo de confianza al 95% de los *counts*·min^{-1} registrados por los tres diferentes ejes de los monitores y el VM. El efecto de la localización del monitor (cadera derecha e izquierda) sobre los *counts*·min^{-1} registrados por los monitores se examinó mediante una ANOVA de medidas repetidas de 2 vías (localización x condición) en cada uno de los ejes y en el VM. Cuando se violó el supuesto de esfericidad se aplicó el factor de corrección de Greenhouse-Geisser. En el caso de existir resultados significativos, se utilizó como test poc-hoc el test de Bonferroni para la comparación de los mismos por pares. Además, se realizó el análisis de Bland-Altman entre la localización izquierda y derecha de los monitores (57). Se usó un análisis T-Test por pares para analizar si existían diferencias significativas en las BIAS entre las dos localizaciones. Por último, se examinó la asociación entre la diferencia y la magnitud de la medición (análisis de heterocedasticidad) mediante un análisis de regresión en cada eje y VM, introduciendo como variable dependiente la diferencia entre los *counts* de la localización derecha menos la localización izquierda y como variable independiente el valor promedio [(*counts* derecha + *counts* izquierda)/2] (58).

Todos los análisis estadísticos se realizaron con el programa PASW (Predictive Analysis Software, v. 18.0, SPSS Inc., Chicago, IL, EE.UU.). Para disminuir la posibilidad de cometer un error tipo I, los análisis de comparación múltiple se corrigieron mediante el método de Bonferroni, en el cual el umbral del valor de P es obtenido dividiendo 0.05 por el número total de comparaciones (59).

3.2.3. Protocolo fase III: Evaluación de la precisión de las ecuaciones publicadas y calibración del acelerómetro GT3X en distintos grupos de edad

Participaron 97 sujetos y según su edad se dividieron en tres grupos:

- 31 jóvenes (12 niñas) de entre 12-16 años (14.7±1.0). Con un peso de 59.6±8.9 kg y una altura de 168.2±6.6 cm.
- 31 adultos (15 mujeres) de entre 40-55 años (47.1±3.5). (Peso: 65.0±16.7 kg y altura: 168.0±10.0 cm).
- 35 personas mayores (22 mujeres) de entre 65-80 años (71.9±5.4). (Peso: 71.9±5.4 kg y altura: 160.9±7.69 cm).

Todos ellos firmaron un consentimiento informado para participar en el estudio. Los jóvenes fueron reclutados del mismo Instituto de Educación Secundaria Obligatoria, los adultos de la misma Universidad y de distintos centros de fitness, y las personas mayores de distintos centros sociales. Todos los sujetos vivían en la misma ciudad. Los criterios de exclusión fueron tener cualquier lesión musculoesquelética o cualquier enfermedad cardiovascular que pudieran afectar al desarrollo de actividades físicas o comprometer su salud. Los participantes también se excluyeron si tenían otra contraindicación para desarrollar actividad física o tomaban algún medicamento que pudiera alterar su tasa metabólica. Todos los participantes completaron previamente el cuestionario PAR-Q. Se excluyeron del estudio un total de 3 personas mayores y 2 adultos porque respondieron "si" a una o más preguntas del cuestionario PAR-Q.

El diseño del estudio tuvo una potencia estadística del 80% para detectar diferencias entre la media del grupo y un error hipotético medio de 0.65 METs con un nivel de significación (alpha) de 0.05 (dos colas).

3 monitores GT3X (4.1.0 versión de Firmware) se programaron e inicializaron simultáneamente (1 s *epoch*). Cada participante eligió de forma aleatoria uno de los monitores para colocarlo en su cadera derecha de forma segura utilizando un cinturón elástico. Dos investigadores comprobaron la posición del monitor antes y después de cada condición. El protocolo consistió en desarrollar 6 condiciones de 10 min de

duración cada una con un descanso entre ellas de al menos 5 min. Las condiciones fueron: (i) reposo, (ii) caminar a 3 $km{\cdot}h^{-1}$, (iii) caminar a 5 $km{\cdot}h^{-1}$, (iv) caminar/correr a 7 $km{\cdot}h^{-1}$, (v) correr a 9 $km{\cdot}h^{-1}$ y (vi) sentarse-levantarse de una silla de manera continua (30 veces por minuto). Por razones de seguridad, las personas mayores no desarrollaron condiciones de intensidad mayor o igual a caminar/correr a 7 $km{\cdot}h^{-1}$. El consumo de oxígeno se midió "respiración a respiración" en cada condición utilizando el método de calorimetría indirecta. Las respiraciones incorrectas ocasionales (como por ejemplo toser, hablar o estornudar) se eliminaron del conjunto de datos cuando su valor excedía al triple del valor de la desviación estándar de la media, la cual era calculada utilizando el promedio de dos intervalos de registro previos y dos posteriores (60).

Análisis estadísticos

Los valores de *counts* para cada condición se obtuvieron realizando el promedio de *counts* registrados en los 4 minutos centrales de cada condición para cada eje (Y, X, Z y *VM*). Así mismo, el valor del gasto energético (METs) medido mediante calorimetría indirecta en cada condición se obtuvo de la misma manera. El valor de METs de cada sujeto se calculó dividiendo el VO_2 de cada condición por el valor individual de gasto metabólico en reposo (registrado antes de comenzar las sesiones). Para determinar el efecto del eje en los *counts* registrados en cada condición se utilizó una ANOVA de dos vías (condición x eje). Cuando se violó el supuesto de esfericidad se aplicó el factor de corrección de Greenhouse-Geisser. En el caso de existir resultados significativos, se utilizó como test poc-hoc el test de Bonferroni para la comparación de los mismos por pares.

A continuación se detallan los análisis estadísticos por objetivo:

(i) Comparación entre gasto energético estimado utilizando las ecuaciones existentes para el acelerómetro GT3X y el gasto energético medido mediante calorimetría indirecta.

Para comparar el gasto energético registrado mediante calorimetría indirecta en cada condición en cada grupo de edad se utilizó un test ANOVA de medidas repetidas de una vía. Además, se utilizó un test ANOVA de medidas repetidas de tres vías [METs (calorimetría indirecta y estimada), grupo de edad y condición] para comparar el gasto energético (METs) estimado empleando los *counts* del acelerómetro GT3X y el registrado mediante calorimetría energética en cada grupo de edad. El test de Bonferroni se utilizó como test poc-hoc para la comparación por pares en el caso de existir resultados significativos. El grado de concordancia (BIAS), la desviación estándar de la BIAS y el límite de concordancia al 95% entre el gasto energético estimado utilizando los *counts* del GT3X y medido mediante calorimetría indirecta se calcularon mediante el análisis Bland-Altman (57).

La precisión de las ecuaciones

previamente publicadas para estimar gasto calórico utilizando el acelerómetro GT3X se determinó examinando la BIAS, la desviación estándar de la BIAS y los límites de concordancia al 95% para cada gráfica de Bland-Altman. Las ecuaciones estudiadas fueron: *"Work-energy Theorem"* (14) [kcal·min^{-1}=0.000019·*counts* (*counts*·min^{-1})·masa corporal (kg)], *"Combined equation"* (14) (si los *counts* son menores o iguales 1952 *counts*·min^{-1} se utiliza la ecuación *"Work-energy Theorem"*, si son mayores se utiliza la ecuación de Freedson (14) [kcal·min^{-1}=0.000094·*counts* (*counts*·min^{-1})+0.1346·masa corporal (kg)-7.37418)] y, finalmente, la ecuación definida por Sasaki et al. (41) (METs=0.000863·*counts* VM+0.668876.

(ii) Definición de nuevas ecuaciones para estimar gasto calórico en jóvenes, adultos y mayores.

Para determinar las nuevas ecuaciones y predecir los METs a partir de los *counts* del VM en cada uno de los grupos de edad se utilizó un análisis de regresión lineal. Posteriormente, la precisión de las nuevas ecuaciones fue evaluada calculando la BIAS, la desviación estándar y los límites de concordancia al 95% para cada análisis de Bland-Altman. Se llevó a cabo una validación cruzada dejando uno fuera (*leave-one-out*) para evaluar si las nuevas ecuaciones podrían ser generalizadas a otro conjunto de datos independientes. Finalmente, la asociación entre la diferencia y la magnitud de la medición (análisis de heterocedasticidad) se examinó por un análisis de regresión, introduciendo la diferencia del gasto energético medido mediante calorimetría indirecta y el estimado a partir de las nuevas ecuaciones como variable dependiente y el valor promedio [(calorimetría indirecta+estimado)/2] como variable independiente (58).

(iii) Determinación de valores de cut-points utilizando los counts del VM para clasificar niveles de actividad física en distintos grupos de edad.

Normalmente, los niveles de intensidad de actividad física se definen utilizando valores determinados de METs (5) (intensidad moderada: 3.00-5.99 METs; intensidad vigorosa: 6.00-8.99 METs e intensidad muy vigorosa: ≥9 METs). El modelo matemático utilizado para construir la ecuación estimadora de METs a partir de los *counts* del VM fue una red neuronal artificial. Una red neuronal artificial es un modelo matemático que simula alguna de las propiedades observadas en el sistema nervioso desarrollando un aprendizaje biológico adaptativo. En los últimos años esta técnica está cobrando gran interés en el área de acelerometría, siendo una de las aconsejadas para los estudios de calibración (35, 61). Los cut-points de definen teniendo en cuenta los valores de METs que definen la clasificación del nivel de intensidad de actividad física (5). Se definieron cuatro redes neuronales artificiales, una para cada grupo. La primera capa de cada red neuronal artificial (capa de entrada) corresponde con la variable independiente (*counts* del VM), mientras que la tercera capa (capa de salida) corresponde con la variable dependiente

(METs). La capa intermedia, que es oculta (tres capas ocultas en cada red neuronal artificial), consiste en todas las posibles conexiones entre la capa de entrada y la de salida (figura 4). La función de activación para cada capa oculta y cada nódulo fue *lineal*, y la función calculada por la unidad oculta fue una *función logística*. Para obtener los pesos sinápticos de cada red neuronal artificial se utilizó el algoritmo de propagación hacia atrás (*back-propagation*) (62). El valor de los parámetros del algoritmo fue de 0.2 para el ratio de aprendizaje. El entrenamiento de la red neuronal se detuvo cuando la suma de los cuadrados de los errores (SSE) cayó por debajo de 0.00001 (63).

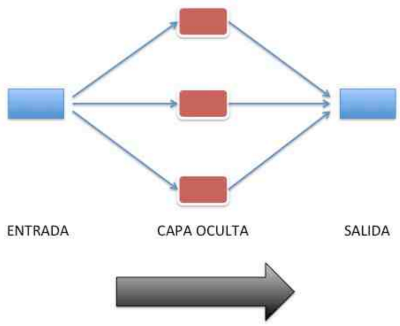

Figura 4. Esquema de las Redes Neuronales Artificiales utilizadas.

El área bajo la curva ROC (Característica Operativa del Receptor), la sensibilidad y la especificidad (64) fueron también calculadas para evaluar la precisión de los nuevos *cut-points* clasificando el nivel de intensidad de actividad física.

Todos los análisis estadísticos se realizaron con el programa PASW (Predictive Analysis Software, v. 18.0, SPSS Inc., Chicago, IL, EE.UU.). El nivel de significatividad se definió en $P \leq 0.05$. Los modelos de redes neuronales artificiales fueron definidos utilizando el programa RSNNS (65) y la potencia estadística del diseño de nuestro estudio fue calculada utilizando el programa estadístico StatMate, versión 2.0 (GraphPad, San Diego, EE.UU.).

4. Resumen global de los resultados

4.1. Fase I: validación mecánica. Fiabilidad técnica del acelerómetro GT3X

Los *counts* aumentaban a medida que aumentaba la frecuencia de movimiento. El nivel de *counts* de cada frecuencia en cada uno de los ejes se muestra en la tabla 2. Los resultados del test ANOVA de dos factores (eje x frecuencia) mostraron un efecto significativo de la frecuencia, el eje y la interacción frecuencia x eje ($P<0.01$). Los tests Post hoc revelaron una diferencia significativa entre los tres ejes a 10.2 Hz.

Además, los *counts* fueron significativamente más bajos a 1.1 Hz comparados con el resto de frecuencias en cada uno de los ejes ($P<0.01$). Únicamente los *counts* del eje Z a 10.2 Hz fueron significativamente diferentes comparados con los *counts* del resto de frecuencias.

Los valores del CV para cada eje y frecuencia se muestran en la tabla 3. El valor más alto y el más bajo, independientemente del eje, corresponden con 10.2 Hz y 3.1 Hz respectivamente.

Tabla 2. Valores de los counts (counts·min-1) en cada una de las frecuencias utilizadas en cada uno de los ejes

	Eje		
Frecuencia (Hz)	Y	X	Z
1.1	18.5 ± 37.3	0.5 ± 1.3	11.5 ± 17.2
2.1	2335 ± 73 [a]	2525 ± 250 [a]	2528 ± 234 [a]
3.1	3428 ± 75 [a,b]	3424 ± 40 [a,b,c]	3417 ± 51 [a,b,c]
4.1	3515 ± 128 [a,b]	3609 ± 273 [a,b,c]	3554 ± 240 [a,b,c]
10.2	3948 ± 1343 [a,b]	2154 ± 1076 [a.d]	5521 ± 1390 [a,b,d,e]

Los datos presentados corresponden a la media ± la desviación estándar

[a] $P<0.01$ *vs.* 1.1 Hz en el mismo eje

[b] $P<0.01$ *vs.* 2.1 Hz en el mismo eje

[c] $P<0.01$ *vs.* 10.2 Hz en el mismo eje

[d] $P<0.01$ *vs.* Eje Y en la misma frecuencia

[e] $P<0.01$ *vs.* Eje X en la misma frecuencia

Tabla 3. Coeficiente de variación (%) intra-instrumento de la media de los *counts* registrados en cada eje y frecuencia

	Eje		
Frecuencia (Hz)	Y	X	Z
1.1	18.5 (0.0 – 105.0)	0.4 (0.0 – 4.0)	11.5 (0.0 – 54.0)
2.1	1.3 (0.5 – 2.1)	1.7 (0.6 -3.7)	2.5 (0.6 – 4.9)
3.1	0.8 (0.5 – 1.5)	0.4 (0.6 - 4.9)	0.6 (0.3 – 1.2)
4.1	1.3 (0.6 – 2.3)	0.8 (0.2 – 2.6)	1.1 (0.4 – 2.2)
10.2	27.3 (8.6 – 52.9)	22.5 (2.61 – 48.3)	8.6 (5.1 – 19.5)

Los datos presentados corresponden a la media y al rango (mínimo – máximo)

[a] $P<0.01$ *vs.* 1.1 Hz en el mismo eje

[b] $P<0.01$ *vs.* 2.1 Hz en el mismo eje

[c] $P<0.01$ *vs.* 10.2 Hz en el mismo eje

[d] $P<0.01$ *vs.* Eje Y en la misma frecuencia

[e] $P<0.01$ *vs.* Eje X en la misma frecuencia

El ICC de los *counts* para las distintas frecuencias combinando los tres ejes (Y, X y Z) fue 0.97 ($P<0.001$). Tomando cada eje de manera independiente se obtuvieron unos valores de ICC de 0.98, 0.99 y 0.98 para el eje Y, X y Z respectivamente ($P<0.001$).

Para los tres ejes, el mayor y menor valor de CVinter fue a 1.1 Hz y 2.2 Hz respectivamente, como se puede apreciar en la tabla 4.

Tabla 4. Coeficiente de variación (%) inter-instrumento de la media de los *counts* registrados en cada eje y frecuencia

	Eje		
Frecuencia (Hz)	Y	X	Z
1.1	201.8	287.0	149.4
2.1	3.1	9.9	9.2
3.1	2.2	1.2	1.5
4.1	3.7	7.6	6.8
10.2	67.3	99.5	52.6
Media general	55.6	81	43.9

4.2. Fase II: validación del acelerómetro GT3X durante actividades físicas estandarizadas. Fiabilidad intermonitor del acelerómetro GT3X

La figura 5 muestra la media de los valores y la desviación estándar de los *counts*·min^{-1} para cada condición en cada eje y en cada localización (derecha e izquierda). Hubo un efecto significativo del factor condición (*P*<0.001) en todos los ejes (con el fin de simplificar la exposición de los resultados, no se muestran los resultados del test post hoc debido al gran número de diferencias significativas).

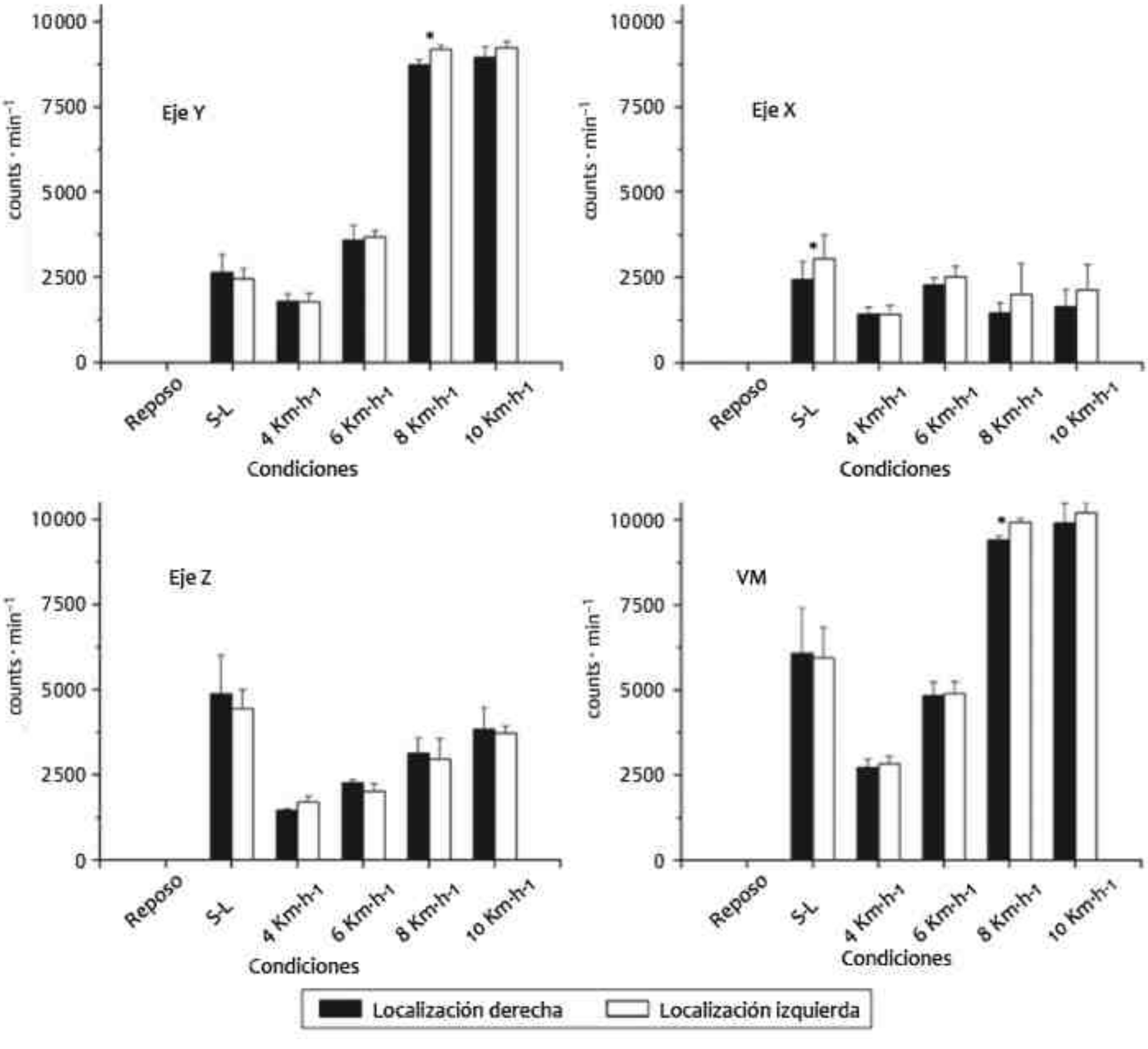

Figura 5. *Counts* por condición. Expresados en *counts*·min^{-1}, media ± desviación estándar. * Significativamente diferente entre la localización derecha e izquierda, misma condición y eje (P<0.001). S-L: sentarse y levantarse; VM, vector magnitud.

ICC

Los valores de ICC se muestran en la tabla 5. Con respecto a cada eje, cabe destacar que: (i) los valores de ICC para el eje Y oscilaron entre 0.933 y 0.998, (ii) para el eje X entre 0.933 y 0.998, con mejores valores para la localización en la cadera izquierda que en la derecha para todas las condiciones, (iii) para el eje Z también fluctuaron entre 0.985-0.997, con valores más altos de ICC en la localización derecha respecto de la izquierda para todas las condiciones excepto para caminar a 4 y 6 km·h^{-1}, (iv) los valores para el VM se encontraron entre 0.946 y 0.988, siendo valores mayores para la localización derecha comparada con la izquierda en todas las condiciones salvo caminando a 6 km·h^{-1}.

CVinter

En la siguiente tabla (tabla 6) se muestra el CVinter de los *counts* para cada condición, eje y localización. El análisis de CVinter para la condición de descanso se omitió debido a bajo valor de *counts* registrados. Con respecto al CVinter en cada eje cabe destacar que: (i) en el eje Y los valores oscilaron entre 20.4 a 1.4% correspondiendo el valor más pequeño de variación corriendo a 8 km·h^{-1} en ambas localizaciones, (ii) en el eje X se mostraron altos valores de variación (9.1-45%), siendo los valores para la localización derecha menores que para la izquierda, (iii) para el eje Z los valores en la condición sentarse-levantarse fueron los más elevados en ambas localizaciones; el CVinter en la localización derecha fueron menores que en la izquierda en todas las

Tabla 5. Coeficientes correlación intraclase (ICC) por eje y condición.

Eje	Localización	Sentarse y levantarse	4 km·h^{-1}	6 km·h^{-1}	8 km·h^{-1}	10 km·h^{-1}
Y	Derecha	0.993	0.995	0.998	0.997	0.997
	Izquierda	0.996	0.950	0.996	0.991	0.925
X	Derecha	0.976	0.991	0.989	0.978	0.933
	Izquierda	0.984	0.998	0.994	0.994	0.947
Z	Derecha	0.996	0.994	0.994	0.997	0.996
	Izquierda	0.992	0.996	0.995	0.994	0.985
VM	Derecha	0.991	0.987	0.997	0.993	0.983
	Izquierda	0.984	0.984	0.998	0.982	0.946

$P < 0.01$ para todos los valores ICC.

Tabla 6. Coeficiente de variación intermonitor (CVinter, %) por eje y condición.

Eje	Localización	Sentarse y levantarse	4 km·h^{-1}	6 km·h^{-1}	8 km·h^{-1}	10 km·h^{-1}
Y	Derecha	20.4	12.7	12.3	1.6	3.4
	Izquierda	12.3	14.5	4.5	1.4	2.1
X	Derecha	21.6	12.8	9.1	19.9	29.9
	Izquierda	22.5	18.4	12.3	45.3	34.3
Z	Derecha	23.2	2.2	3.5	13.7	16.3
	Izquierda	12.4	10.6	10.7	19.6	5.5
VM	Derecha	22.3	9.2	8.1	1.1	5.8
	Izquierda	14.9	7.0	6.5	1.1	2.7

condiciones excepto para sentarse y levantarse y 10 km·h^{-1}, (iv) para el VM todos los valores fueron menores o iguales a 14.9% excepto para la localización derecha en la condición de sentarse-levantarse (23.0%), la localización izquierda mostró CVinter mayores que la localización derecha para todas las condiciones. Además al igual que en el eje Y, los valores más bajos de CVinter para el VM correspondieron con la condición de 8 km·h^{-1}, en ambas localizaciones.

Intervalo de confianza del 95% (CI)

Los valores del 95% CI para los *counts* registrados por el acelerómetro GT3X indican la variación de esta variable alrededor de la media (tabla 7).

4.3. Fase III: evaluación de la precisión de ecuaciones conocidas y calibración del acelerómetro GT3X en distintos grupos de edad. Validación y determinación de cut-points para la evaluación del nivel de actividad física

Los *counts* y los METs registrados en cada eje incrementaron a medida que se incrementó la intensidad (figuras 6 y 7).

Para una mejor comprensión se ordenarán los resultados por sub-objetivos.

(i) Comparación entre gasto energético estimado utilizando las ecuaciones existentes para el acelerómetro GT3X y el gasto energético medido mediante calorimetría indirecta.

Se compararon los valores de gasto energético estimados a partir de las ecuaciones descritas en el manual de Actigraph (14) y la definida por Sasaki et al. (41) con los valores de gasto energético medidos mediante calorimetría indirecta. Comparando los resultados de las BIAS (calorimetría indirecta-estimada) y los límites de concordancia al 95%, y siguiendo el criterio utilizado por Crouter et al. (66), la ecuación menos precisa fue la "*Work-energy Theorem*" para adultos utilizando los *counts* del VM (BIAS=-1.856; SD=2.848; LOA=-7.437 – 3.725). La más precisa fue la ecuación "*Combined*" en niños utilizando los *counts* del VM (BIAS=-0.053; SD=1.776;LOA=-3.534 - 3.482).

Tabla 7. Intervalo de confianza del 95% (inferior-superior) de los *counts* por eje, localización y condición.

Eje	Localización	Sentarse y levantarse	4 km·h^{-1}	6 km·h^{-1}	8 km·h^{-1}	10 km·h^{-1}
Y	Derecha	2188 – 3086	1598 – 1976	3217 – 3957	8628 – 8859	8701 – 9209
	Izquierda	2198 – 2703	1553 – 1982	3545 – 3824	9091 – 9301	9080 – 9398
X	Derecha	2000 – 2882	1285 – 1594	2112 – 2458	1213 – 1698	1237 – 2061
	Izquierda	2483 – 3632	1192 – 1624	2262 – 2779	1243 – 2761	1523 – 2749
Z	Derecha	3941 – 5834	1431 – 1485	2199 – 2331	2777 – 3492	3321 – 4367
	Izquierda	3982 – 4905	1544 – 1845	1837 – 2198	2482 – 3455	3547 – 3887
VM	Derecha	4940 – 7201	2520 – 2939	4505 – 5156	9342 – 9511	9427 – 10391
	Izquierda	5195 – 6679	2681 – 3015	4641 – 5175	9847 - 10023	9993 – 10453

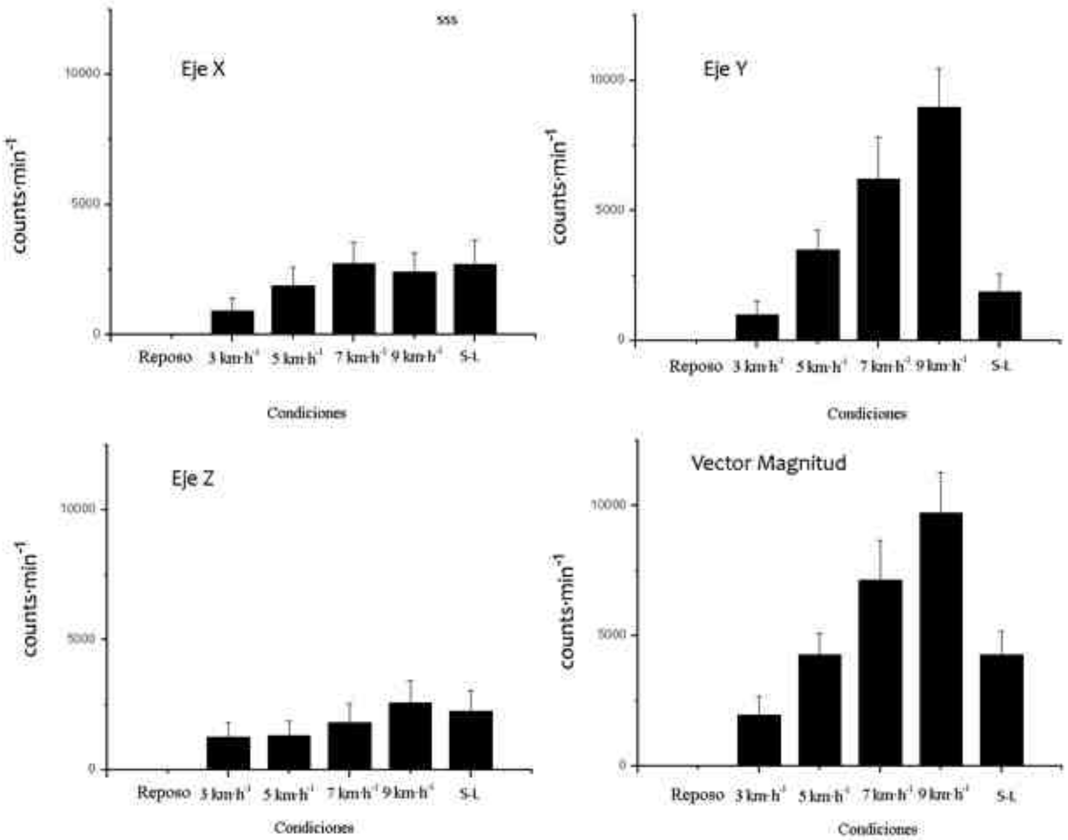

Figura 6. *Counts* (*counts*·min^{-1}) por eje y condición para todos los sujetos combinados (media ± desviación estándar). S-L: sentarse y levantarse.

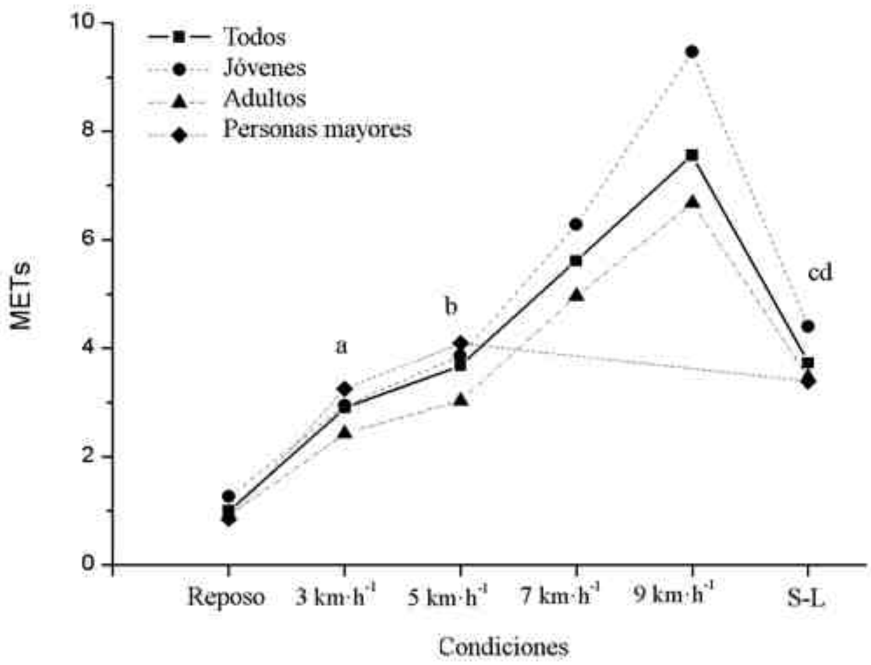

Figura 7. *Counts* (*counts*·min^{-1}) por eje y condición para todos los participantes y por grupo de edad (media). S-L: sentarse y levantarse.

(ii) Definición de nuevas ecuaciones para estimar gasto calórico en jóvenes, adultos y mayores.

En la tabla 8 se muestran las nuevas ecuaciones propuestas para estimar gasto energético empleando los *counts* del VM y del eje Y. Utilizando los *counts* del VM se obtuvo una estimación más precisa de gasto energético que usando los *counts* del eje Y.

Los análisis de validación cruzada dejando un sujeto fuera confirmaron los coeficientes de cada variable y la constante en cada grupo de edad. La media del error y la desviación estándar del error fueron -1.758 y 1.980 para el grupo de todos los sujetos, -1.571 y 1.864 en jóvenes, -2.152 y 1.97 en adultos, y 0.011 y 1.114 en mayores respectivamente.

Los análisis de heterocedasticidad muestran una asociación significante positiva (R=0.528, *P*=0.01) entre la diferencia y la media del gasto energético medido con calorimetría indirecta y el gasto energético estimado utilizando los *counts* del VM y las nuevas ecuaciones para el grupo de todos los sujetos de forma combinada. Además se encontró una correlación positiva en jóvenes (R=0.558, *P*=0.01) y adultos (R=0.536, *P*=0.01), pero no para personas mayores (R=0.043, *P*=0.615). En la figura 8 se muestran las diferencias en METs entre el gasto energético estimado con las nuevas ecuaciones y el gasto energético determinado mediante calorimetría indirecta.

Tabla 8. Nuevas ecuaciones propuestas.

Grupo	Eje	Ecuación	R	R^2	EEE (±)	RECM
Todos (n=97; 49 mujeres)	Y	*METs = 3.14153 + 0.00057·counts eje Y – 0.01380·IMC – 0.00606·E*	0.78	0.60	1.45	1.45
	VM	*METs = 2.7406 + 0.00056 · counts del VM– 0.008542·E – 0.01380·BM*	0.78	0.66	1.40	1.40
Jóvenes (n=31;12 niñas)	Y	*METs = 2.118079 + 0.000662· counts del eje Y*	0.81	0.65	1.56	1.55
	VM	*METs = 1.546618 + 0.000658·counts del VM*	0.83	0.68	1.49	1.49
Adultos (n=31;15 mujeres)	Y	*METs (kcal·min^{-1}) = 3.4002 + 0.00053·counts eje Y– 0.05564·IMC+ 1.2789·S*	0.82	0.67	1.28	1.27
	VM	*METs = 2.8323 + 0.00054· counts del VM – 0.05912·IMC +1.4410·S*	0.84	0.71	1.21	1.20
Personas mayores (n=35; 22 mujeres)	Y	*METs (kcal·min^{-1}) = 2.8867 + 0.00067·counts del eje Y– 0.6807·S*	0.50	0.36	1.18	1.17
	VM	*METs = 2.5878 + 0.00047· counts del VM – 0.6453·S*	0.64	0.41	1.14	1.13

R: coeficiente de correlación
R^2: coeficiente de determinación
EEE: error estándar de la estimación
RECM: raíz cuadrada del error cuadrático medio
IMC: índice de masa corporal (kg·m^2)
E: edad (años)
S: sexo (1 mujer, 2 hombre)

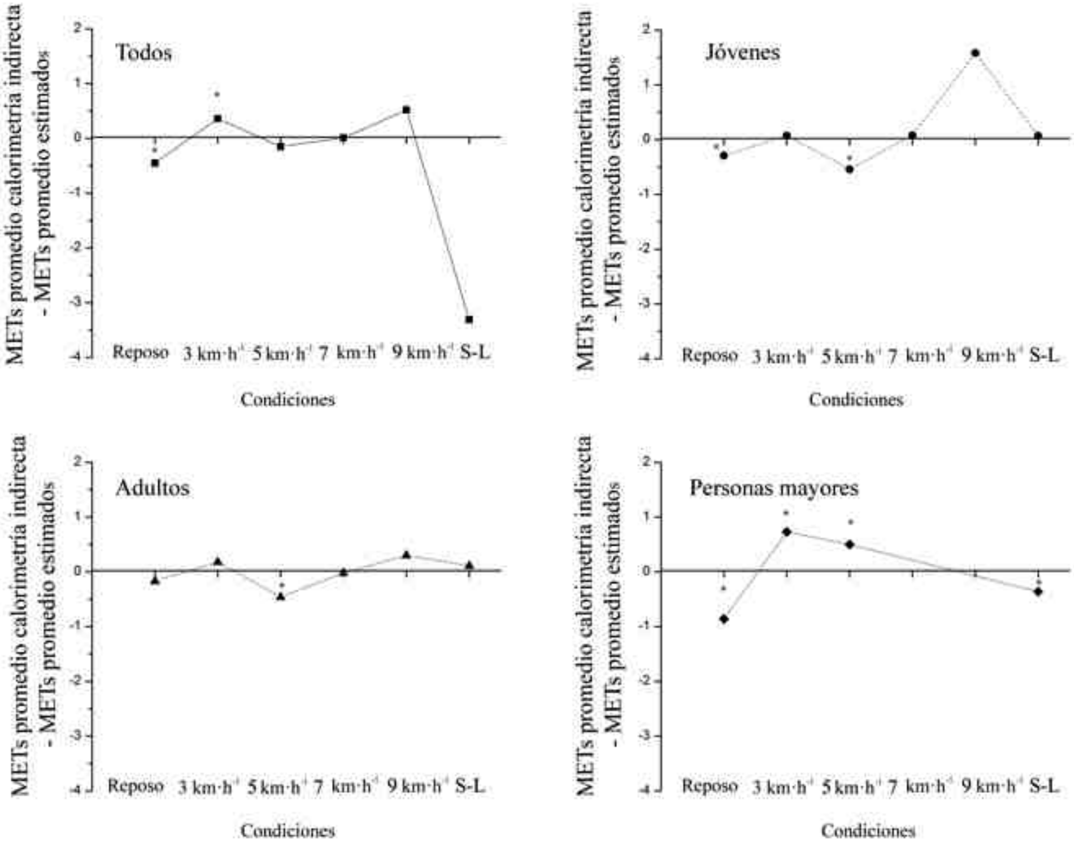

Figura 8. Gasto calórico expresado en METs determinado mediante calorimetría indirecta *vs* gasto calórico (METs) estimado a partir del GT3X en cada grupo. *Significativamente diferente gasto calórico de calorimetría indirecta *vs* estimado, $P<0.05$.

(iii) Determinación de valores de cut-points utilizando los counts del VM para clasificar niveles de actividad física en distintos grupos de edad.

Los valores de cut-points (*counts* del VM) se establecieron utilizando un modelo artificial de red neuronal (tabla 9).

Tabla 9. *Cut-points* definidos para los *counts* registrados por el Vector Magnitud (VM) en cada uno de los grupos.

MET	Todos	Jóvenes	Adultos	P. Mayores
3	1480	2114	3208	2751
6	8505	6548	8565	9359
9	10500	11490	11593	--------

Los resultados para el análisis de las curvas ROC (área bajo la curva, sensibilidad y especificidad) para los *cut-points* propuestos se presentan en la tabla 10.

Tabla 10. Valor bajo el área de la curva ROC, sensibilidad (%) y especificidad (%) de los *cut-points* propuestos en cada grupo e intensidad de actividad.

		Lig.	Mod.	Vig.	M.Vig
Todos	Área	0.8	0.7	0.6	0.6
	Sen (%)	89.9	56.6	24.4	21.4
	Esp (%)	27.1	21.2	24.4	10.6
Jóvenes	Área	0.8	0.7	0.7	0.6
	Sen (%)	80.9	66.7	49.1	43
	Esp (%)	18.1	22.3	19	18.6
Adultos	Área	0.8	0.6	0.7	0.6
	Sen (%)	84.6	52.2	46	43
	Esp (%)	28.1	22.3	20	21
Personas mayores	Área	0.7	0.7	-------	-------
	Sen (%)	68.5	72.5		
	Esp (%)	27.5	31.5		

Área bajo la curva ROC, sen: sensibilidad (%) y esp: especificidad (%).

Lig., ligera; mod., moderada; vig. vigorosa y m.vig. muy vigorosa.

5. Discusión

En general, todos los resultados en conjunto sugieren que el acelerómetro Actigraph GT3X puede ser una herramienta útil para estimar el gasto calórico y los niveles de actividad física en humanos; aunque es necesario que se utilicen ecuaciones y *cut-points* específicos para distintos grupos de edad.

Los datos obtenidos de la validación mecánica del acelerómetro (Fase I) nos aportan una evidencia preliminar sobre la fiabilidad del GT3X; estos resultados indican que dicho acelerómetro tiene una alta intra e inter fiabilidad en el rango de frecuencias de movimiento comprendido entre 2.1 y 4.1 Hz.

Los *counts* registrados (de 0.5 a 5521 *counts* $\cdot min^{-1}$) bajo las condiciones mecánicas que fueron seleccionadas (ver tabla 1) estaban dentro del rango fisiológico del movimiento humano. Kozey et al. (53) estudiaron la relación entre los *counts* registrados por un acelerómetro (modelo GT1M) y el gasto energético (METs) de una serie de actividades diarias muy comunes. Los valores de *counts* registrados fueron desde 11 *counts*$\cdot min^{-1}$ (lavar platos a mano) hasta 7490 *counts*$\cdot min^{-1}$ (correr en una tapiz rodante a 8.028 $km\cdot h^{-1}$ con una inclinación positiva del 3%), lo cual equivale a 1.9 y 9.7 METs respectivamente. Sasaki et al. en 2011 (41) compararon los *counts* del acelerómetro GT1M y GT3X durante actividades de marcha en un tapiz rodante obteniendo ~4000 *counts*$\cdot min^{-1}$, ~6000 *counts*$\cdot min^{-1}$ y ~10000 *counts*$\cdot min^{-1}$ a 4.8, 6.4 y 9.7 $km\cdot h^{-1}$ respectivamente.

Tal como muestran los valores obtenidos por el CVintra, el acelerómetro GT3X presenta una buena fiabilidad general intra-instrumento. Estos valores son similares a los obtenidos por Esliger et al. (17) para el Actigraph 7164 (CVintra=4.1%) y para el Actical (CVintra=0.4%) bajo distintas condiciones de vibración (desde 1.5 a 2.5 Hz con una amplitud comprendida entre 19.8 y 62.1 mm). Además, a diferencia de los estudios anteriores, nosotros utilizamos dos métodos estadísticos adicionales diferentes para analizar la fiabilidad inter-instrumento, como son el CVinter y el ICC. El CVinter varió considerablemente entre las distintas condiciones de vibración, siendo los valores más bajos de ICC los obtenidos en las condiciones con frecuencias de movimiento entre 2.1-4.1 Hz (≤9%). La mayoría de las actividades físicas diarias más comunes están comprendidas entre 0.3 y 3.5 Hz (67), como por ejemplo caminar despacio y correr rápido que corresponde a 0.75 Hz (68) y ≤4Hz (69), respectivamente. Los valores de CVinter observados entre 2.1-4.1 Hz son ligeramente más altos que los encontrados previamente por otros autores con otros acelerómetros. Por ejemplo, Eliger et al. y Sun et al. describieron valores inferiores a 7.7% para el Actigraph 7164 (17, 67). Rothney et al. evaluando tres generaciones diferentes de acelerómetros Actigraph (7164, 71256 y GT1M) obtuvieron valores próximos a 0.5% para frecuencias menores de 7 Hz (24). En el estudio de Fairweather et al. (22), se sometieron cuatro monitores Actigraph 7164 a una oscilación mecánica de 2.0 Hz y 30 mm de amplitud, los autores observaron una fiabilidad mayor que en nuestro estudio (CVinter de 3%). Esta discrepancia entre estudios puede deberse a que en el mencionado estudio solamente utilizaron 4 acelerómetros y en el nuestro utilizamos 10 y también por el hecho de que solo utilizaron una única condición (2.0 Hz y 30 mm de amplitud) mientras que en nuestro estudio se utilizaron cinco condiciones de vibración diferentes (Ver tabla 1). En nuestro estudio, el CVinter fue >149% en la frecuencia más baja (1.1Hz), lo cual está en concordancia con el informe de Rothney et al. (24) en el cual se evaluó la precisión de tres generaciones de acelerómetros Actigraph (7164, 71256 y GT1M). Además, Brage et al. (21) sometieron seis acelerómetros Actigraph 7164 a una serie de aceleraciones y frecuencias utilizando una plataforma rotatoria. Los valores de CVinter mostraron también una gran variación inter-instrumento (>100%) en las aceleraciones más bajas (< 1 $m \cdot s^{-2}$), mejorando los resultados en las aceleraciones comprendidas entre 2-3 $m \cdot s^{-2}$ obteniendo valores de 5% y aumentando de nuevo los valores de variación hasta ~12% a partir de 5 $m \cdot s^{-2}$.

Los valores de ICC en nuestro estudio a través de las frecuencias en los 3 ejes (Y, X y Z) fueron relativamente altos (55), y están en consonancia con otros estudios (23, 54). Metcalf et al. (23) describieron ICCs entre 0.71 y 0.99 para el CSA bajo condiciones mecánicas. Mientras que Powell et al. (54) obtuvieron un ICC constante de 0.99 para todos los ejes del RT3.

Antes de evaluar los niveles de actividad física en estudios epidemiológicos es necesario conocer la fiabilidad intermonitor del acelerómetro que se utilizará, por ello decidimos analizar dicho parámetro (Fase II) y nuestro estudio fue el primero que se ha publicado en este sentido. La variabilidad intermonitor debe ser la mínima para permitir una correcta comparación entre individuos (26) que se han monitorizado con el mismo modelo de acelerómetro pero no con la misma unidad física o monitor. Para evaluar la variabilidad intermonitor es importante evaluar el comportamiento del acelerómetro en diferentes tipos de actividades físicas y de distinta intensidad. Como se esperaba, a medida que se incrementaba la intensidad de las actividades, los monitores registraron en todos sus ejes un mayor número de *counts*, excepto en el eje X a 6 $km \cdot h^{-1}$. Como se puede ver en la figura 4, los *counts* registrados fueron significantemente diferentes entre condiciones, lo cual confirma que de manera general el acelerómetro GT3X muestra una capacidad suficiente para diferenciar entre sí modos e intensidades de actividad física distintas.

No se observaron diferencias significativas entre los *counts* a 8 y 10 $km \cdot h^{-1}$ en ninguno de los ejes ni en el VM. Varios autores han descrito previamente la dificultad de otros modelos de acelerómetros para diferenciar entre velocidades similares o superiores a 8 $km \cdot h^{-1}$ ya que la aceleración vertical normalmente permanece casi constante a estas velocidades de carrera (24, 26, 56, 70). El hecho de no encontrar diferencias entre 8 y 10 km·h^{-1} en ningún eje ni en el VM podría deberse a este hecho. Los resultados del ICC fueron muy altos en todos los planos (≥0.925 y en el VM ≥0.946). Sin embargo, hay que tener en cuenta que el análisis de ICC no permite descubrir diferencias específicas absolutas en cada velocidad (70). Por esta razón es importante estudiar otros indicadores estadísticos como el CV y el intervalo de confianza al 95%. Se debe señalar en relación con estos análisis que el GT3X muestra una alta fiabilidad en todos los planos, sin embargo el eje X mostró el mayor rango de CV (9.1-45.3) mientras que el eje Y y el VM mostraron una baja variabilidad comparada con la de los otros ejes. Por tanto, estamos de acuerdo con otros autores como por ejemplo Howe et al. (71) que concluyen que la tecnología de los acelerómetros triaxiales está aún bajo desarrollo y no proporciona una ventaja importante sobre los acelerómetros uniaxiales (71, 72). Nuestros resultados muestran que los valores de variación aumentan a medida que se incrementa la intensidad de la actividad física en el eje X y en el eje Z, lo cual concuerda con los resultados de otros estudios de investigación que utilizaron el acelerómetro RT3 (26). El hecho de que en el eje Y la variación del CV disminuye a medida que aumenta la intensidad se describió también previamente con el acelerómetro RT3 (54).

Mientras unos autores (26) no encontraron diferencias significativas en la localización del acelerómetro utilizando el RT3, otros estudios que utilizaron otros modelos de acelerómetros Actigraph mostraron diferencias significativas entre la localización derecha e izquierda en la cadera (22, 73); al igual que nosotros, que encontramos diferencias significativas para la localización del acelerómetro (derecha *vs* izquierda) en el eje X a 6 km·h^{-1} y durante la condición de sentarse y levantarse. En el eje Y a 8 km·h^{-1} y en el eje VM a 4 y 8 km·h^{-1}. Por tanto, los acelerómetros Actigraph GT3X podrían ser más sensibles a las diferencias entre derecha-izquierda de la cadera, es por ello importante recomendar que el acelerómetro GT3X sea colocado en el mismo lado de la cadera para obtener resultados fiables (19) tanto en la misma persona para distintos días, como para diferentes individuos.

Hasta el momento no existe ningún estudio en el que se evalúe la precisión de las ecuaciones publicadas en el manual del fabricante Actigraph (14) para estimar el gasto energético utilizando los *counts* del acelerómetro GT3X, tampoco se ha comprobado si existen diferencias en la exactitud para estimar gasto calórico al utilizar los *counts* registrados del VM o solamente los del eje Y. Nuestros resultados mostraron que estas ecuaciones no son aparentemente precisas para estimar gasto calórico independientemente del eje que se utilice. Para el grupo de jóvenes la utilización de los *counts* del VM junto con la ecuación *"Combined equation"* resultó ser la más precisa. Para adultos fue la "*Combined equation*" y los *counts* del eje Y. Finalmente, para personas mayores la predicción más precisa se encontró empleando la ecuación "*Work-energy Theorem equation*" la cual utiliza los *counts* del eje Y. Utilizando la ecuación propuesta por Sasaki et al. (41) con *counts* provenientes del VM los resultados más precisos se obtuvieron cuando se combinaron todos los grupos de edad y no en un grupo en concreto. Cuando se comparan estos resultados con otros estudios previos (37, 61, 74-76) parece necesario desarrollar nuevas ecuaciones para estimar gasto calórico.

Para determinar cuál de las nuevas ecuaciones obtenidas con el análisis de regresión lineal fue la más precisa, utilizamos el análisis de Bland y Altman en cada uno de los grupos de edad (57). Los resultados muestran como las nuevas ecuaciones propuestas son más precisas que las del manual Actigraph o que la propuesta por Sasaki et al.. Además, si se utilizan los *counts* del VM se obtienen unos resultados más precisos que si se utilizan los del eje Y. En cambio Howe et al. (71) concluyeron que la utilización del VM no proporciona una estimación más precisa de gasto calórico que la utilización de los *counts* registrados en el eje Y. Los resultados obtenidos con el GT3X indican que este acelerómetro es una buena herramienta para estimar gasto calórico durante actividades de caminar en tapiz rodante, excepto en personas mayores. Además, excepto el grupo de más avanzada edad, la utilización de ecuaciones específicas por grupo de edad resultaron ser más precisas que la ecuación general para toda la muestra. Fehling et al. (16) encontraron que, en personas mayores, el acelerómetro Caltrac sobreestima el gasto calórico caminando sobre tapiz rodante, mientras que el acelerómetro Tritrac lo subestima. Strath et al. (49) ha puesto de manifiesto recientemente que existe una falta de ecuaciones que proporcionen una estimación más precisa del gasto calórico en personas mayores.

Sasaki et al. han comparado el número de *counts* registrados por el eje Y de los acelerómetros GT1M y GT3X (41) no encontrando diferencias entre ellos. Sin embargo, nosotros hemos comprobado como la utilización de los *counts* del VM para estimar gasto calórico es más precisa que los *counts* del eje Y. Por ello, creemos que la utilización de los *counts* del VM registrados por el GT3X para estimar el nivel de actividad física también será más precisa. Será por tanto necesario definir unos cut-points para los *counts* del VM en cada grupo de edad (tabla 11). Sasaki et al. (41) establecieron los siguientes cut-points utilizando los *counts* del VM en jóvenes adultos (26.9±7.7 años): para actividades moderadas (3-5.99) de 2690 a 6166 *counts*$\cdot$min^{-1}, para actividades vigorosas (6-8.99) de 6167 a 9642 counts$\cdot$min^{-1} y para actividades muy vigorosas (≥9 METs) >9642 *counts*$\cdot$min^{-1}. Los autores incluyeron en su trabajo la media de las diferencias entre los METs reales y los estimados (-0.3, -0.4 y 0.7 METs a 4.8, 6.4 y 9.7 km$\cdot$h^{-1}, respectivamente), pero no detallaron el valor de la desviación estándar de la BIAS. Para los tres grupos de edad de nuestro estudio, las diferencias de las medias fueron menores que las descritas por Sasaki et al. (41), lo cual puede explicarse porque ellos evaluaron *counts* y METs utilizando solamente 3 condiciones (4.8, 6.4 y 9.7 $km \cdot h^{-1}$) y también por los análisis estadísticos utilizados. Después de revisar la literatura, creemos que nuestro estudio es pionero en la utilización de un modelo de red neuronal para definir los valores de *cut-points*, suponiendo un punto de inflexión en la metodología utilizada hasta la fecha para ello.

Todas las condiciones evaluadas en el presente estudio eras actividades estandarizadas en condiciones de laboratorio(tapiz rodante y sentarse-levantarse de una silla) siendo estas a su vez la mayor limitación de nuestro diseño. Futuros estudios deben comprobar y evaluar las ecuaciones aquí propuestas para su utilización en condiciones de la vida diaria (77).

6. Conclusiones

- Bajo condiciones mecánicas controladas, se observó una alta fiabilidad general intra e inter instrumento entre las frecuencias de movimiento comprendidas entre 2.1 y 4.1 Hz, lo que apoya el uso de este instrumento en estudios donde se pretende evaluar el nivel de actividad física en humanos.

- La localización del acelerómetro GT3X sobre la cadera derecha o izquierda puede afectar el registro de datos. Sin embargo, es necesario ampliar la muestra de estudio para determinarlo con claridad.

- El acelerómetro GT3X parece ser una herramienta útil para estimar gasto calórico y puede ser lo suficientemente sensible para diferenciar entre niveles de intensidad de actividad física, al menos en condiciones estandarizadas de laboratorio.

- El acelerómetro triaxial GT3X representa un paso adelante en la tecnología triaxial para la estimación del gasto calórico, sin embargo la utilización del VM no supone una mejora importante respecto a fiabilidad en comparación con anteriores versiones uniaxiales de acelerómetros Actigraph.

- La ecuación "Combined equation" del software Actilife para estimar METs (14) utilizando los counts del GT3X proporcionó mejores resultados que el resto de ecuaciones previamente publicadas. Sin embargo, las nuevas ecuaciones aquí desarrolladas aportan una estimación de gasto calórico mucho más precisa para cada uno de los grupos de edad.

- Los nuevos cut-points, calculados utilizando redes neuronales artificiales y específicos para el acelerómetro GT3X, aquí propuestos para cada grupo de edad proporcionan una herramienta útil para determinar los niveles de actividad física.

7. Conclusions

- Our data indicate that the GT3X accelerometer has high intra- and inter-instrument reliability at frequencies between 2.1 and 4.1Hz. Our findings provide preliminary evidence on the reliability of this device. This supports the use of this instrument in studies that aim to assess the level of physical activity in humans.

- The hip monitor placement (right or left) may influence the accelerometer output. Future research should be performed with several subjects, including both right- and left-handed people, to corroborate the influence of monitor placement.

- In conclusion, overall the GT3X appears to be an accurate tool for EE prediction, which proved sufficiently sensitive to discriminate between different intensities of PA, at least for activities performed in a laboratory setting.

- Compared to more traditional uniaxial or biaxial devices, the GT3X triaxial accelerometer shows a technical step forward estimating EE during human PA. However, the use of VM is not a major improvement on reliability compared to previous versions Actigraph uniaxial accelerometer.

- The equation of the Actilife software called "Combined equation" estimating METs from the GT3X *counts* (14) gave better results than the other previously published equations. However, the new equations proposed here provide an estimate of energy expenditure much more accurate for each of the groups.

- The new proposed specific cut-points, that were calculated using artificial neural network, for each age group provide a useful tool to determine physical activity levels with the accelerometer GT3X.

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Anexos

Abreviaturas

ADC: convertidor de analógico a digital
Curva ROC: Característica Operativa del Receptor
CV: coeficiente de variación
CVinter: coeficiente de variación interinstrumento
CVintra: coeficiente de variación intraisntrumento
E: edad (años)
EEE: error estándar de la estimación
Hz: Hercios
ICC: coeficiente de correlación intraclase
IMC: índice de masa corporal (kg·m2);
km·h^{-1}: kilómetros por hora
LOA: limites de concordancia
m·s^{-2}: metros por segundo
MET: unidad metabólica
min: minuto
mm: milímetro
PASW: Predictive Analysis Software
R: coeficiente de correlación
R^2: coeficiente de determinación

Relación de tablas y figuras

participantes y por grupo de edad (media)

Figura 8. Gasto calórico expresado en METs determinado mediante calorimetría indirecta *vs* gasto calórico (METs) estimado a partir del GT3X en cada grupo

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Communication

Technical variability of the GT3X accelerometer

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ABSTRACT

To analyze the intra- and inter-instrument reliability of the ActiGraph GT3X accelerometer using a vibration table on each orthogonal axis and at five frequencies of motion. Ten GT3X units were subjected to a specific vibration using a motorized vibration table along the vertical, horizontal right–left and horizontal front–back axis, and at 1.1, 2.1, 3.1, 4.1 and 10.2 Hz. The 5 min data for each frequency were analyzed separately for frequency, axis effects, and inter- and intra-instrument variability. We found overall high intra-and inter-instrument reliability for the GT3X accelerometer at frequencies between 2.1 and 4.1 Hz. For frequencies ranging between 2.1 and 4.1 Hz, the intra-instrument coefficient of variation was ≤2.5%. The inter-instrument coefficient of variation ranged widely along axes and frequencies, with the lowest values (≤9%) corresponding to 2.1–4.1 Hz. The intra-class correlation coefficient for activity counts across frequencies and for all axes was 0.97. Overall, our findings support the use of the GT3X accelerometer as an accurate tool to estimate free-living physical activity, at least within those frequencies that are common to most types of human daily activities.

1. Introduction

Activity monitors (i.e. accelerometers) are commonly used for assessing free-living physical activity (PA) in humans [1]. Among the different types of commercially available accelerometers, the ActiGraph accelerometers have been widely used in epidemiological studies [2]; these monitors have undergone several hardware and software revisions since the original 'Computer Science Applications' (CSA) model was created. In 2000, ActiGraph launched to the market the GT1M model, a device containing the ADXL320 acceleration sensor (a monolithic surface micromachined accelerometer with an integrated circuit polysilicon chip, dual-axis microelectromechanical system) which has a full-scale acceleration range of ±5 Gs. However, ActiGraph-specified restrictions allow detecting accelerations only in the 0.05–2 Gs range [3]. A new ActiGraph generation was developed in 2009, the tri-axial GT3X accelerometer, using the ADXL335 accelerometer, a triaxial capacitive microelectromechanical system sensor with a full-scale range of ±3 Gs [3].

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Owing to the widespread use of ActiGraph accelerometers for PA determination in epidemiological and clinical studies, it is a question of relevance to assess the reliability of these devices. Several studies have analyzed the inter- and intra-instrument variability of previous generations of ActiGraph monitors [4–8], yet the inter- and intra-instrument variability of the GT3X unit remains to be investigated. The use of mechanical oscillators to assess the accuracy of accelerometers prior to studies on humans during actual PA, offers important methodological advantages such as the large number of accelerations that can be generated, the ability to record data simultaneously from multiple monitors, and the reproducibility of between-trial oscillations.

It was the main purpose of this study to examine the intra- and inter-instrument reliability of the GT3X accelerometer using a vibration plate in each orthogonal axis and at five frequencies of motion.

2. Methods

2.1. Description of the ActiGraph GT3X activity monitor

The GT3X monitor (ActiGraph, Pensacola, FL, USA) is lightweight (27 g), compact (dimensions of 3.8 cm × 3.7 cm × 1.8 cm) and rechargeable (i.e. lithium polymer battery-powered) [9]. It must

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be worn at the waist using a belt clip or elastic belt. It uses a solid state tri-axial accelerometer to collect motion data on three axes, i.e. vertical (*Y*), horizontal right–left (*X*) and horizontal front–back axis (*Z*). The ActiGraph also includes the vector summed value $\sqrt{X^2+Y^2+Z^2}$, known as 'vector magnitude' [9]. The GT3X measures and records time-varying accelerations in the range of ~0.05–2.5 Gs [9]. The accelerometer output is digitized by a twelve-bit analog to digital convertor (ADC) at a rate of 30 Hz [9]. Once digitized, the signal passes through a digital filter that band-limits the accelerometer to the frequency range of 0.25–2.5 Hz [9]. Each sample is summed over an 'epoch', that is, a specific interval of time which typically corresponds to 60 s except in younger populations, in which shorter epochs are recommended [10]. The output of the ActiGraph is given in 'counts', with one count equaling 16.6 miliGs s^{-1} at 0.75 Hz [9]. Activity counts, which are the result of summing the absolute values of the sampled change in acceleration measured during the time period (*dA*/*dL*), represent a quantitative measure of activity over time. The counts obtained in a given time period are linearly related to the intensity of the subject's PA during this period.

2.2. Study design

One study researcher randomly selected ten GT3X units from a sample of fifty brand new units. The ten GT3X units were initialized via a computer interface. Each GT3X device was mounted securely and firmly on a vibration table avoiding unwanted movements or accelerometer misalignment. The vibration table was driven by a trifasic motor (JL 712-2 type) (Fig. 1), which was accurately programmed by a compact inverter type (FRNO.75C1S, FRENIC-Mini Series; Fuji Electric, Japan).

Each GT3X device was placed on the vibration table so that vibration would only occur along the *Y*-axis (Fig. 1A). Various acceleration conditions were applied to the devices by altering the frequency of oscillation. Vibration of the table commenced at a frequency of 1.1 Hz and thereafter increased to 2.1, 3.1, 4.1 and 10.2 Hz respectively. Each frequency was maintained for 7 min. The initial and final minute of each 7 min period were discarded, so that five complete minutes at each frequency were used for analyses. Amplitude was identical in the five testing conditions (0.040 m). The five testing conditions were administered in random order to minimize the possibility of an order effect. This procedure was repeated with the accelerometer placed so that the vibration would only occur along the *X* (Fig. 1B) and *Z*-axis (Fig. 1C). The five different frequencies of motion chosen were selected to provide a range of physiologically relevant accelerometer counts (from light to vigorous) within the limitations of the vibration table (Table 1) [11], because it is important to use a range of activity count values similar to those corresponding to actual human motion. Although higher frequencies are possibly out of the range of human motion, the results obtained with these 'non-physiological' frequencies are still relevant to assess the technical variability of the monitor [12]. The apparatus was run for 5 min at each of the five frequencies before each testing session, as performed elsewhere [12]. To generate all accelerations in this study, we selected a vertical shaker with a frequency range of 66–612(±2) rpm (1.1–10.2 Hz), which thus allowed for a reasonable simulation of repetitive human movements such as gait [8,13]. The vibration table was driven by an electric motor (JL 712-2 type), controlled by a compact inverter type (FRNO.75C1S, FRENIC-Mini Series; Fuji Electric, Japan).

Table 1
Description on the five different testing conditions used.

Condition	Frequency (Hz)	Acceleration (Gs)
1	1.1	1.083
2	2.1	1.087
3	3.1	1.093
4	4.1	1.164
5	10.2	4.143

2.3. Statistical analysis

All statistical analyses were performed with PASW (Predictive Analytics Software, v. 18.0, SPSS Inc., Chicago, IL, USA). Data are presented as means ± standard deviation (SD), unless otherwise stated.

To determine the frequency and axis effects, we used a two-way ANOVA test with repeated measures on axis (*X*, *Y*, and *Z*) and frequency (1.1, 2.1, 3.1, 4.1, and 10.2 Hz). When the assumptions of sphericity were violated, we applied the Greenhouse–Geisser correction factor.

For intra-instrument reliability assessment, we calculated the coefficient of variation (CVintra) of each device from the replicate minutes (1–5 min) within each condition. This minute-by-minute variability characterizes the accelerometer's ability to consistently measure the given condition rendered by the vibration table. This is a noteworthy distinction of our design compared with previous research in the field that has focused on analyzing within-accelerometer variability [7,12]. Thus, less variability (i.e. less technological error) is expected with the methods we used here because no trial effect was present. To assess the inter-instrument reliability, we used intra-class correlation coefficients (ICC) with a two-way random model for absolute agreement, in order to determine the relationship between accelerometers for all three axes (*X*, *Y* and *Z*) combined and separately. An ICC close to 1 represents good repeatability [14]. We also calculated the inter-instrument coefficient of variation (CVinter) for each axis at each frequency (SD/mean).

Table 2
Activity counts at each axis and frequency.

Frequency (Hz)	Axis		
	Y (activity counts min^{-1})	*X* (activity counts min^{-1})	*Z* (activity counts min^{-1})
1.1	18.5 ± 37.3	0.5 ± 1.3	11.5 ± 17.2
2.1	2335 ± 73[a]	2525 ± 250[a]	2528 ± 234[a]
3.1	3428 ± 75[a,b]	3424 ± 40[a,b,c]	3417 ± 51[a,b,c]
4.1	3515 ± 128[a,b]	3609 ± 273[a,b,c]	3554 ± 240[a,b,c]
10.2	3948 ± 1343[a,b]	2154 ± 1076[a,d]	5521 ± 1390[a,b,d,e]

Data are means ± standard deviation.
[a] $P < 0.01$ vs. 1.1 Hz at the same axis.
[b] $P < 0.01$ vs. 2.1 Hz at the same axis.
[c] $P < 0.01$ vs. 10.2 Hz at the same axis.
[d] $P < 0.01$ vs. the *Y*-axis at the same frequency.
[e] $P < 0.01$ vs. the *X*-axis at the same frequency.

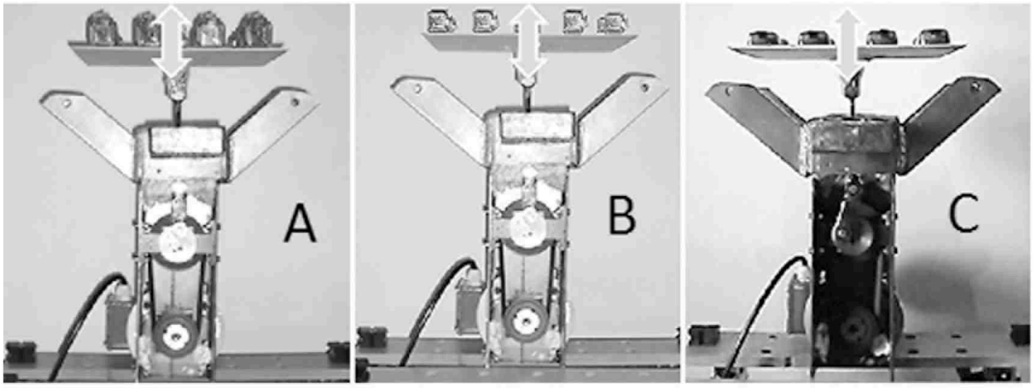

Fig. 1. Vibration table setup along the Y (1A), X (1B), and Z (1C) axis. The *arrow* indicates the direction of movement of the vibration table.

3. Results

3.1. Frequency and axis effects

Activity count output increased in all axes as frequency increased (Table 2). The results of the two-factor ANOVA for activity counts revealed a significant frequency, axis, and frequency * axis interaction effect (all $P < 0.01$). Post hoc tests revealed a significant difference between the three axes at 10.2 Hz. Also, the activity counts were significantly lower at 1.1 Hz compared with the rest of frequencies at each of the three axes ($P < 0.01$), whereas the activity counts were significantly different at 10.2 Hz compared with the rest of frequencies only for the Z-axis ($P < 0.01$).

3.2. Intra-instrument variability

The CVintra values for each axis and frequency are shown in Table 3. The highest and lowest CVintra values corresponded to 10.2 Hz and 3.1 Hz respectively, irrespective of the axis.

3.3. Inter-instrument variability

The ICC for activity counts across frequencies for the three axes combined was 0.97 ($P < 0.001$). The ICC for activity counts across all frequencies for the Y, X, and Z axes was 0.98, 0.99, and 0.98 respectively (all $P < 0.001$). For the three axes, CVinter was highest and lowest at 1.1 Hz and 2.2 Hz respectively (Table 4).

4. Discussion

Our data indicate that the GT3X accelerometer has high intra- and inter-instrument reliability at frequencies between 2.1 and 4.1 Hz. Although further research is necessary to assess the reliability of this device in free-living conditions, our findings provide preliminary evidence on the reliability of this device. The average accelerometer output in the present study ranged the physiological range of common human motion, that is from 0.5 to 5521 counts min^{-1}. A recent study [15] examined the relationship between accelerometer output and metabolic equivalents (METs) for a range of common activities. The average accelerometer output ranged from 11 counts min^{-1} (hand-dish washing) to 7490 counts min^{-1} (treadmill running at 2.23 m s^{-1} with a 3% inclination), which equals to 1.9 and 9.7 METs respectively. Sasaki et al. [16] compared activity counts obtained with the ActiGraph models GT3X and GT1M during treadmill walking/running at three velocities: 4.8 km h^{-1} (corresponding to ~4000 counts min^{-1}), 6.4 km h^{-1} (~6000 counts min^{-1}), and 9.7 km h^{-1} (~10,000 counts min^{-1}).

As expected, increasing frequencies resulted in increases in the count output generated in the Y (vertical) and Z-axis (horizontal front–back). However, increasing movement frequency produced seemingly counterintuitive results in the X-axis (horizontal right–left) (Table 2). This finding is in agreement with those reported by Esliger and Tremblay with the RT3 accelerometer: as frequency continuously increased, RT3 counts firstly decreased and then increased [5]. To note is that accelerometers are accelerometer-based PA monitors, not instruments that merely record acceleration.

Our results showed an overall good intra-instrument reliability of the GT3X accelerometer, as shown by the CVintra values we obtained. The observed CVintra are similar to those reported by Esliger and colleagues [5] when the 7164 ActiGraph (CVintra = 4.1%) and Actical accelerometers (CVintra = 0.4%) were vibrated from 1.5 to 2.5 Hz on a shaker with a 0.0198–0.0621 m amplitude. We used two different statistical methods to assess inter-instrument reliability, i.e. CVinter and ICC. The CVinter ranged widely along axes and frequencies, with the lowest values (≤9%) corresponding to 2.1–4.1 Hz. The major energy band for most types of daily PA lies between 0.3 and 3.5 Hz [17], e.g. 0.75 Hz for slow-walking [18] and ≤4 Hz for fast running [19]. The CVinter values observed for 2.1–4.1 Hz are slightly higher than those previously reported with

Table 3
Intra-instrument coefficient of variation for the mean activity counts recorded at each axis and frequency.

Frequency (Hz)	Axis		
	Y (%)	X (%)	Z (%)
1.1	18.5% (0.0–105.0)	0.4% (0.0–4.0)	11.5% (0.0–54.0)
2.1	1.3% (0.5–2.1)	1.7% (0.6–3.7)	2.5% (0.6–4.9)
3.1	0.8% (0.5–1.5)	0.4% (0.6–4.9)	0.6% (0.3–1.2)
4.1	1.3% (0.6–2.3)	0.8% (0.2–2.6)	1.1% (0.4–2.2)
10.2	27.3% (8.6–52.9)	22.5% (2.61–48.3)	8.6% (5.1–19.5)

Data are shown as mean and range (min–max).

Table 4
Inter-instrument coefficient of variation for the mean activity counts recorded at each axis and frequency.

Frequency (Hz)	Axis		
	Y (%)	X (%)	Z (%)
1.1	201.8%	287.0%	149.4%
2.1	3.1%	9.9%	9.2%
3.1	2.2%	1.2%	1.5%
4.1	3.7%	7.6%	6.8%
10.2	67.3%	99.5%	52.6%
Overall mean	55.6%	81.0%	43.9%

other accelerometers, e.g. less than 5.3% for fast and medium speeds on a turntable with the CSA (7164 model) uniaxial accelerometer [7], less than 7.7% with the ActiGraph 7164 model [5], or values in the order of 0.55% for all frequencies >0.7 Hz with three generations of ActiGraph accelerometers (7164, 71256, and GT1M) [8]. In the study by Fairweather et al. [6], four ActiGraph 7164 model units were oscillated at 2.0 Hz and 0.030 m amplitude using a mechanical system, and they observed a higher reliability (CVinter of 3%) than in our study. The discrepancy between studies could be explained by the relatively low number of accelerometers tested by Fairweather et al. [6] ($n = 4$, vs. $n = 10$ units in our study) and by the fact that only one testing condition (2.0 Hz and 0.030 m amplitude) was used (vs. 5 frequencies in our study). In the present study, the CVinter was >149% at the lowest frequency (1.1 Hz), which is in agreement with a report assessing the accuracy of three generations of ActiGraph accelerometers (7164, 71256, and GT1M) [8]. Brage et al. [4] exposed six ActiGraph accelerometers (Model 7164) to a host of acceleration and frequency conditions via a dual rotating-wheel setup. The CVinter showed large inter-instrument variation (>100%) for the lowest accelerations ($<1\,\mathrm{m\,s^{-2}}$), decreasing to the minimum level of 5% at $2–3\,\mathrm{m\,s^{-2}}$, and rising again to an average of $\sim$12% at $\geq 5\,\mathrm{m\,s^{-2}}$.

In our study the ICC observed across frequencies for the *Y*, *X*, and *Z* axes were relatively high [14], and are in agreement by those reported by other studies [7,12].

In summary, we observed overall high intra-and inter-instrument reliability of the GT3X accelerometer at frequencies between 2.1 and 4.1 Hz, which provides preliminary support for the use of this device in studies assessing human PA. However, further research is necessary to assess the reliability of the GT3X at higher frequencies, and especially with human subjects during actual free-living PA.

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Conflict of interest

None of the authors have any financial and personal relationship with other people or organizations that could inappropriately influence their work.

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Paper II:

"Intermonitor Variability of the GT3X accelerometer"

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Intermonitor Variability of GT3X Accelerometer

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Key words
- physical activity
- activity assessment
- accelerometry
- motion sensor

Abstract

The main purpose of this study was to assess the inter-monitor reliability of the tri-axial GT3X Actigraph accelerometer over a range of physical activities (PA). This device collects motion data on each of the vertical (Y), horizontal right-left (X), and horizontal front-back (Z) axes and also calculates the vector summed value $\sqrt{X^2+Y^2+Z^2}$ known as 'vector magnitude' (VM). 8 GT3X accelerometers were worn at the same time by the same participant. Accelerometers were placed back-to-front, all facing forward and in sets of 4 securely taped together, attached to a belt and allocating each block above either left or right hip at waist level. Inter-monitor reliability was assessed during 6 conditions: rest, walking (4 and 6 km·h^{-1}), running (8 and 10 km·h^{-1}) and repeated sit-to-stand (40 times·min^{-1}). The intra-class correlation coefficients were high for X, Y and Z axes (i.e., all ≥0.925) and for VM (≥0.946). In conclusion, we found good inter-instrument reliability of the GT3X accelerometer across all planes, yet our results also suggest that the X and Z axes do not provide further benefits over the 'traditional' Y-axis to assess the movement in typical PA.

Introduction

Activity monitors (i.e., accelerometers) are commonly used for measuring free-living physical activity (PA) in humans [7]. Despite their limitations, e.g., inability to assess the metabolic cost associated with standing, load carrying, static work, vertical lift, changes in gradient and most upper body movements [2,14], accelerometers are valid tools for PA assessment [9,10,20]. Actigraph accelerometers have been widely used over the last 10 years to assess PA in free-living populations [6]. A tri-axial model was recently developed, the GT3X activity monitor (Actigraph, Pensacola; FL, USA), which collects motion data on 3 axes, i.e., vertical (Y), horizontal right-left (X), and horizontal front-back (Z).

A design that is commonly used to assess inter-monitor variability is a mechanical device that provides a standardized amount of acceleration [18]. Yet it is important to evaluate the behaviour of the measurements recorded by accelerometers while worn by humans because studies using mechanical devices cannot provide a true evaluation of how accelerometers perform during PA [22].

No published data are available on the reliability and inter-monitor variability of the Actigraph GT3X device during standardized PA. Hence, the main purpose of this study was to investigate the reliability and inter-monitor variability of the GT3X, along each orthogonal axis of motion, over a range of standardized PA.

Methods

Instrumentation

Actigraph GT3X activity monitor

The GT3X (Actigraph, Pensacola, FL, USA) is a lightweight, and compact accelerometer. The unit must be worn at the waist using a belt clip or elastic belt. This tri-axial accelerometer collects motion data on 3 orthogonal axes, known as vertical (Y), horizontal right-left (X), and horizontal front-back axis (Z). The Actigraph GT3X also includes the vector summed value $\sqrt{X^2+Y^2+Z^2}$, known as 'vector magnitude' (VM). This device accurately and consistently records time varying accelerations ranging in magnitude from ~0.05 to 2.5 Gs. Each sample is summed over a user specified interval of time called 'epoch'. A epoch duration of 60 s is generally used in the field and for all vectors that were needed in our study. The output of the Actigraph is in 'counts', with one count equaling 16.6 milliGs per second at 0.75 Hz.

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Activity counts are simply the summation of the absolute values of the sampled change in acceleration (dA/dt) measured during the cycle period. Activity counts represent a quantitative measure of activity over time. Counts in a given cycle are linearly related to the intensity of the subject's PA during this interval of time.

Procedures

The reliability and intermonitor variability of the GT3X was assessed under the following 6 conditions [15]: (i) resting, (ii) walking at 4 $km \cdot h^{-1}$, (iii) walking at 6 $km \cdot h^{-1}$, (iv) running at 8 $km \cdot h^{-1}$, (v) running at 10 $km \cdot h^{-1}$, and (vi) repeated sit-to-stands. Walking and running was performed on an electronically driven treadmill (Powerjog, model JM200, Sport Engineering Ltd., UK) whereas the speed of repeated sit-to-stands (40 $times \cdot min^{-1}$) was controlled with a metronome. Each condition (included resting) was performed for 12 min, with at least a 10-min break between each condition. The first and last minute of each 12-min bout was deleted, leaving 10 min at each condition for each trial. Data output were activity $counts \cdot min^{-1}$ per each orthogonal axis and VM.

8 GT3X accelerometers were randomly used for this study within an available sample of fifty, all of which were 1-month-old. All 8 monitors were tested at the same time on the same subject (male, age 27 years, height 181.0 cm, weigh 76.5 kg), who was recreationally active and without balance or ambulatory disorders. The research project was in accordance with the Declaration of Helsinki, it was approved by the University Review Board and it was in agreement with the ethical standards in sport and exercise science research [11].

The accelerometers were initialized via a computer interface, simultaneously started, and split into 2 sets of 4. The 8 accelerometers were placed back-to-front, all facing forward and in sets of 4 securely taped together [17]. This gave 2 blocks of monitors that were attached to a belt, positioning each block above either the left or right hip at waist level.

Statistical analysis

All statistical analyses were performed with PASW (Predictive Analytics Software, v. 18.0 SPSS Inc., Chicago, IL, USA). Descriptive data (activity $counts \cdot min^{-1}$) are presented as means ± standard deviation (SD).

To examine the reliability and the inter-monitor variability within accelerometers for each condition (rest, sit-stand, 4, 6, 8 or 10 $km \cdot h^{-1}$), we calculated the intra-class correlation coefficients (ICC), coefficient of variation (CV), and 95% confidence intervals (CI) for the accelerometer output (activity $counts \cdot min^{-1}$) obtained on each orthogonal axis and VM.

To study the effect of monitor placement across the aforementioned conditions on activity $counts \cdot min^{-1}$, a 2-way mixed model ANOVA [monitor placement (right or left) x condition (rest, sit-stand, 4, 6, 8 or 10 $km \cdot h^{-1}$)] was used for each orthogonal axis and VM. The Bonferroni test was used to identify significant interactions. Where necessary, degrees of freedom were adjusted according to the Greenhouse Geisser correction due to violation of the assumption of sphericity. Moreover, systematic error (bias or mean inter-monitor differences) and random error (95% limits of agreement, mean difference ± SD of the difference multiplied by 1.96) between right and left monitor placement was determined using Bland and Altman plots [3]. The paired *t*-test was used to analyse significant differences in bias between monitor placements. In addition, the association between the difference and the magnitude of the measurement (i.e., heteroscedasticity) was examined by regression analysis. For the latter analysis, the difference between the activity counts from right and left monitor placement was entered as the dependent variable, whereas the averaged value [(right activity counts + left activity counts)/2] was entered as the independent variable in each axis and VM [1].

In order to minimize the risk of type I error, we corrected the analyses for multiple comparisons using the Bonferroni method, in which the threshold *P*-value is obtained by dividing 0.05 by the number of comparisons [12].

Results

Fig. 1 shows activity $counts \cdot min^{-1}$ for each condition by axis and placement (right and left side). A significant main condition effect ($P<0.001$) was found in all axes (for simplicity purposes, results of post hoc tests are not shown due to the high number of significant differences).

Intra-class correlation coefficients (ICC)

ICC values are shown in **Table 1**. With regards to each axis: (i) Y-axis, ICC values ranged from 0.925 to 0.998; (ii) X-axis, ICC ranged from 0.933 to 0.998, with higher values in left monitor placement compared with right monitor placement for all conditions; (iii) Z-axis, high ICC values were also found (range: 0.985–0.997), with higher ICC in right monitor placement compared with left monitor placement for all conditions except for walking at 4 and 6 $km \cdot h^{-1}$; and (iv) *VM*, the values of ICC ranged from 0.946 to 0.998, being higher in right monitor placement compared with left monitor placement for all conditions except for walking at 6 $km \cdot h^{-1}$.

Intermonitor coefficients of variation (CV inter)

CV inter values are shown in **Table 2**. The CV inter for rest was omitted from the analysis due to the very low mean score. With regards to each axis: (i) Y-axis, CV inter values ranged from 20.4 to 1.4%, with the lowest CV inter value corresponding to running at 8 $km \cdot h^{-1}$, in both monitor placements; (ii) X-axis, CV values were very high among conditions (range: 45.3–9.1%), with right monitor placement eliciting lower values than left placement for all conditions; (iii) Z-axis, for sit-stand condition CV values were the highest in both monitor placements and right monitor placement elicited lower CV values than left monitor placement except for sit-stands and 10 $km \cdot h^{-1}$; and (iv) VM, all the CV values were ≤14.9% except for right monitor placement in sit-stands (23.0%), with left monitor placement eliciting higher values than right monitor placement for all conditions. Similar to Y-axis, the lowest CV inter values in VM corresponded to 8 $km \cdot h^{-1}$, in both monitor placements.

95% confidence intervals (CI)

The values of CI for the accelerometer output illustrating the variation of these variables around the mean are shown in **Table 3**.

Monitor placement

Y-axis

The 2-factor ANOVA showed a significant monitor placement x condition interaction effect on activity $counts \cdot min^{-1}$ ($P<0.001$). Post hoc tests revealed significant differences ($F_{1.53,\ 10.72}=9.818$,

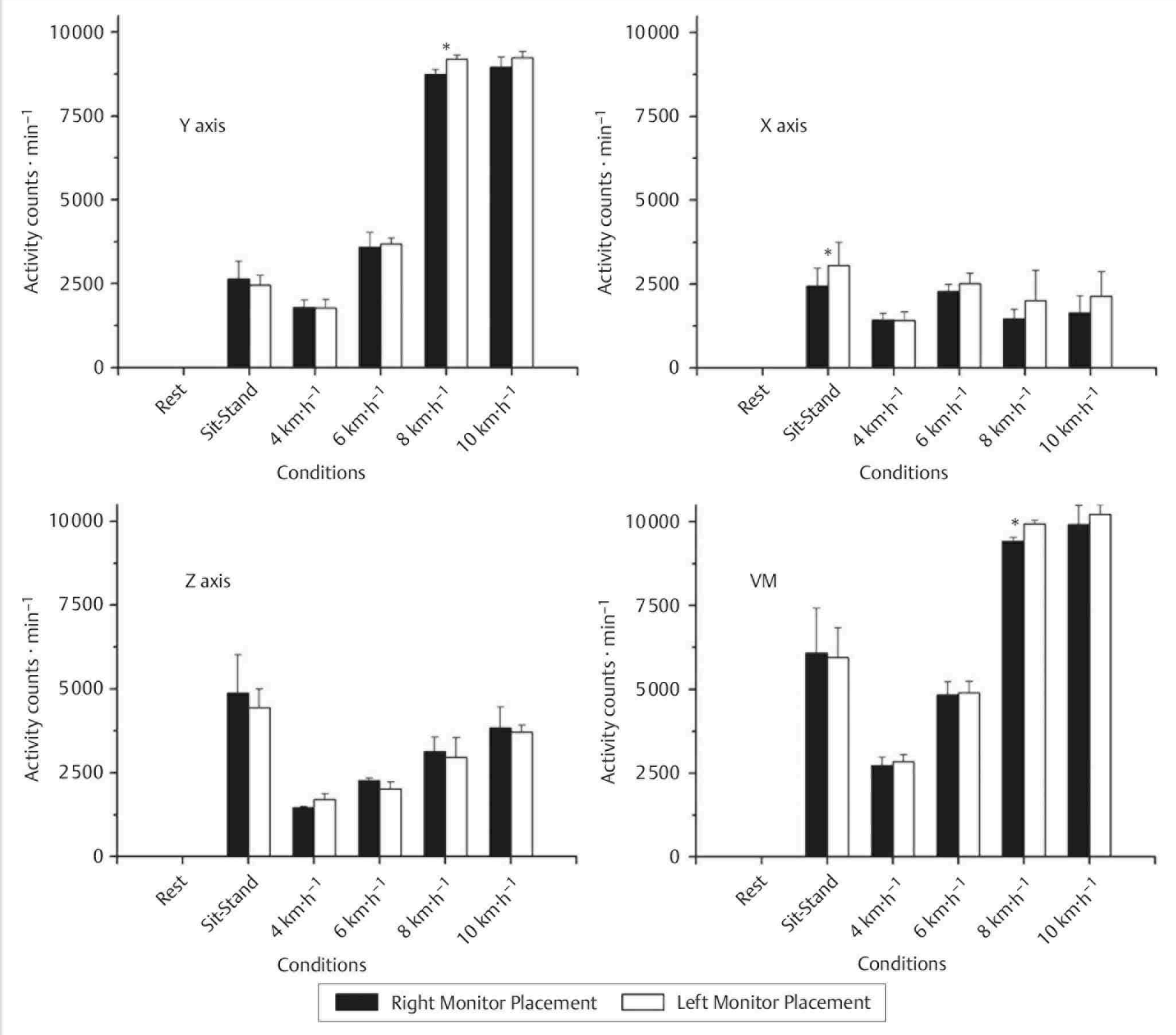

Fig. 1 Activity counts per condition. Expressed in counts.min^{-1}, mean ± SD. *Significantly different between right and left monitor placement, same condition and same axis (P < 0.001). VM, vector magnitude.

Table 1 Intra-class correlation coefficients (ICC) by axis and activities.

	Monitor placement	Sit-Stands	4 km·h^{-1}	6 km·h^{-1}	8 km·h^{-1}	10 km·h^{-1}
Y	Right	0.993	0.995	0.998	0.997	0.997
	Left	0.996	0.950	0.996	0.991	0.925
X	Right	0.976	0.991	0.989	0.978	0.933
	Left	0.984	0.998	0.994	0.994	0.947
Z	Right	0.996	0.994	0.994	0.997	0.996
	Left	0.992	0.996	0.995	0.994	0.985
VM	Right	0.991	0.987	0.997	0.993	0.983
	Left	0.984	0.984	0.998	0.982	0.946

P < 0.01 for all ICC values
VM, vector magnitude

P < 0.001) between right and left monitor placement at 8 km·h^{-1}. The Bland and Altman plots are shown in **Fig. 2a**; the bias was −15.8 ± 540.8 (P = 0.149). The heteroscedasticity analysis showed no significantly negative correlation (R = −0.122, P = 0.454) between the difference and the averaged value of the activity counts from right and left monitor placement.

X-axis

A significant monitor placement x condition interaction effect on activity counts·min^{-1} (P < 0.01) was observed. A significant difference ($F_{1.20,\ 8.38}$ = 3.018, P < 0.01) between monitor placements was observed for the sit-stand activity. The bias

Table 2 Intermonitor coefficients of variation (CV, in %) by axis and activities.

	Monitor placement	Sit-Stands	4 km·h^{-1}	6 km·h^{-1}	8 km·h^{-1}	10 km·h^{-1}
Y	Right	20.4	12.7	12.3	1.6	3.4
	Left	12.3	14.5	4.5	1.4	2.1
X	Right	21.6	12.8	9.1	19.9	29.9
	Left	22.5	18.4	12.3	45.3	34.3
Z	Right	23.2	2.2	3.5	13.7	16.3
	Left	12.4	10.6	10.7	19.6	5.5
VM	Right	22.3	9.2	8.1	1.1	5.8
	Left	14.9	7.0	6.5	1.1	2.7

VM, vector magnitude

Table 3 95 % confidence intervals (lower – upper) of the accelerometer output by axis, monitor placement, and activities.

	Monitor placement	Sit-Stands	4 km·h^{-1}	6 km·h^{-1}	8 km·h^{-1}	10 km·h^{-1}
Y	Right	2188–3086	1598–1976	3217–3957	8628–8859	8701–9209
	Left	2198–2703	1553–1982	3545–3824	9091–9301	9080–9398
X	Right	2000–2882	1285–1594	2112–2458	1213–1698	1237–2061
	Left	2483–3632	1192–1624	2262–2779	1243–2761	1523–2749
Z	Right	3941–5834	1431–1485	2199–2331	2777–3492	3321–4367
	Left	3982–4905	1544–1845	1837–2198	2482–3455	3547–3887
VM	Right	4940–7201	2520–2939	4505–5156	9342–9511	9427–10391
	Left	5195–6679	2681–3015	4641–5175	9847–10023	9993–10453

VM, vector magnitude

was −370±885.5 (P=0.012) (◉ **Fig. 2b**). The heteroscedasticity analysis showed no significant correlation (R=0.298, P=0.071) between the difference and the averaged value of the activity counts from right and left monitor placement.

Z-axis
The 2-factor ANOVA test showed no significant interaction effect on activity counts·min^{-1} ($F_{1.03,\ 7.24}$=3.642, P=0.731). The bias was 149.5±929.6 (P=0.315) (◉ **Fig. 2c**). The heteroscedasticity analysis showed a significant positive correlation (R=0.868, P<0.001) between the difference and the average of the activity counts from right and left monitor placement.

VM
The 2-factor ANOVA test showed a significant monitor placement×condition interaction effect on activity counts·min^{-1} (P<0.001). Post hoc tests revealed significant differences between right and left monitor placement at 8 km·h^{-1} ($F_{1.09,\ 7.64}$=6.040, P<0.001). The bias was −177.1±1064 (P=0.299) (◉ **Fig. 2d**). The heteroscedasticity analysis showed no significant correlation (R=0.077, P=0.637) between the difference and the averaged value of the activity counts from right and left monitor placement.

Discussion

The GT3X is a relatively new Actigraph accelerometer and, to the best of our knowledge, this is the first study analyzing the inter-monitor reliability of this device during standardized PA. Assessing the inter-monitor reliability of an accelerometer is necessary prior to conducting research using this methodology for PA determination; inter-monitor variability should indeed be minimal to allow proper between and within-subject comparisons [17]. It is also important to assess the behaviour of the activity monitor in a range of conditions (i.e., different modes and intensities of PA) as we did in the present study. As expected, the faster speed PA were associated with higher activity output (activity counts·min^{-1}) in all orthogonal axes (X, Y and Z), except for walking at 6 km·h^{-1} in the X-axis. As shown in ◉ **Fig. 1**, the recorded activity counts·min^{-1} were significantly different between each condition, which confirms that overall the GT3X accelerometer shows enough capacity to distinguish different modes and intensities of PA.

We did not observe significant differences between activity counts·min^{-1} at 8 and 10 km·h^{-1} in any of the axes and VM. Several authors reported the difficulty of other accelerometers to discriminate between speeds below or above 8 km·h^{-1} owing to the fact that vertical acceleration usually remains overall constant in walking/running [5, 15, 17, 18]. This could explain the lack of differences we found between 8 and 10 km·h^{-1} in any of the axes and VM. In our study, the ICCs were high across all planes (i.e., all ≥0.925 and in VM≥0.946). It must, however, be noted that the ICC does not allow finding absolute differences specific to each speed [5]. For this reason, it is also important to use other statistical indicators such as the CV and the 95 % CI. With regard to this, although the ICC and CV values for the Y-axis (ranging between 0.925–0.998 and 1.6–20.4 %, respectively), and for VM (0.946–0.998 and 1.1–22.3 %, respectively) indicated lower variability compared with the other axes, it must be emphasized that the GT3X accelerometer showed overall high reliability across all planes. Thus, we agree with other authors, such as Howe et al. [13], in that the technology of tri-axial accelerometers is still under development and does not currently provide major advantages over uni-axial accelerometers [4, 13].

We obtained the highest CV scores (i.e., above 20 % at 8 and 10 km·h^{-1}) for the X-axis. Others showed that the highest CV scores corresponded to the Z-axis when using the tri-axial RT3 accelerometer [17]. On the other hand Trost et al. [19] reported lower CV values for a previous Actigraph model (CSA) (<9 %) compared with those we reported for the GT3X Actigraph during treadmill walking/running (◉ **Table 2**). To bear in mind is

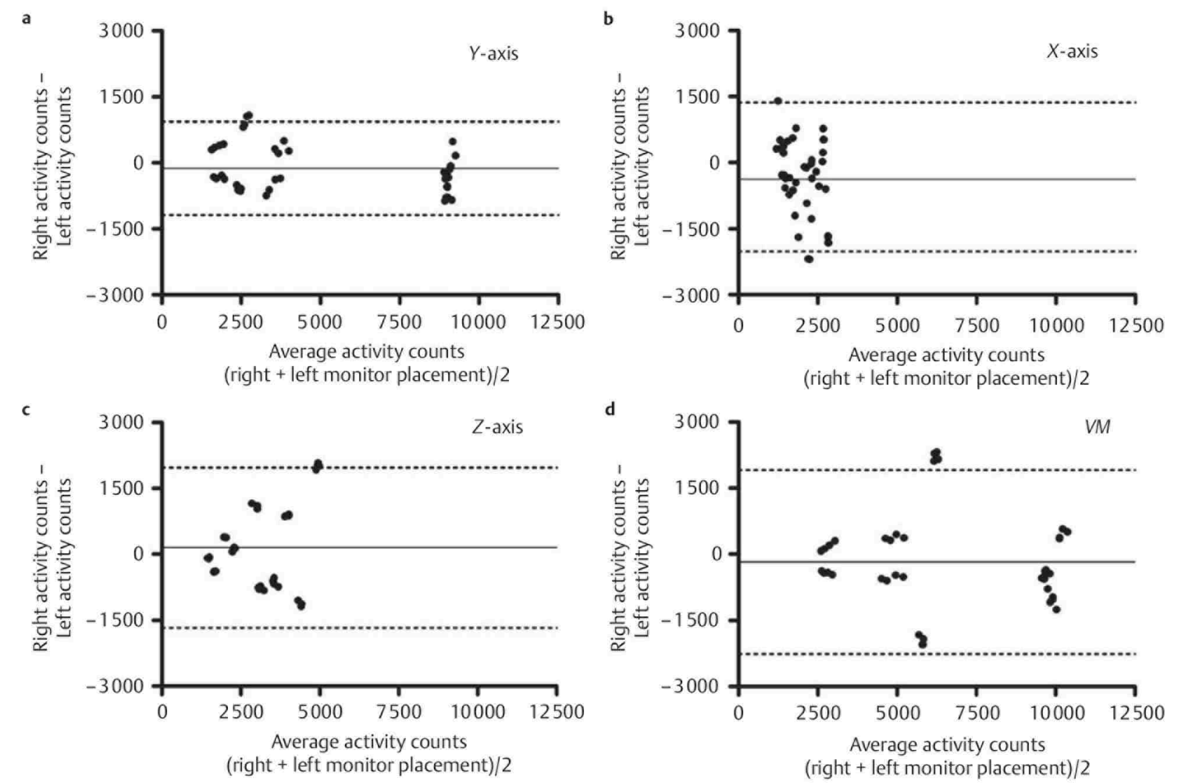

Fig. 2 Bland and Altman Plots in each orthogonal axis (right – left monitor placement). VM, vector magnitude. Straight line: bias; dotted line: 95% limits of agreement.

that Trost et al. used 4 monitor devices and 3 treadmill speeds (3, 4 and 6 $km \cdot h^{-1}$), whereas here we used 8 GT3X monitors at 6 different conditions. Our results showed that the CV increased with increasing PA intensities in the *X* and *Z*-axis, which is in agreement with previous research on the RT3 accelerometer [17]. The fact that CV decreased in the *Y*-axis at higher intensities is also in agreement with previous data on the RT3 accelerometer [16].

Finally, we found significant differences for monitor placement (i.e., right vs. left hip) in the *X*-axis at 6 $km \cdot h^{-1}$ and in sit-stands, in the *Y*-axis at 8 $km \cdot h^{-1}$, and in the VM at 4 and 8 $km \cdot h^{-1}$. While other authors [17] did not report significant differences due to monitor placement using other types of accelerometers (RT3), previous research using Actigraph accelerometers has also shown significant differences between right and left hip placement [8,23]. Thus, Actigraph accelerometers may be more sensitive according to the position on the body where they are placed. It is thus important to recommend that GT3X accelerometers be constantly worn on the same side in order to obtain reliable results [21], both across different individuals and within the same individuals across different days of monitoring. On the other hand, we found no evidence supporting that the width of the random scatter increased or decreased as the general size of the measured $counts \cdot min^{-1}$ increased, i.e., random errors were 'homoscedastic' for all axis and VM, except for the *Z*-axis ($P<0.001$). The paired t-test showed that the mean difference between monitor placements was not significantly different from the null hypothesis of zero difference for all axes, except for the X-axis ($P=0.012$); thus, there was a good agreement for all axes, except for the X-axis. The 'analytical goal' for an acceptable level of agreement in accelerometry research is not clear, but it could be assumed that an acceptable variation would be ~10%. As Bland and Altman indicated [3], an acceptable agreement is more a clinical question independant of statistical issues. Ideally, one should decide the amount of disagreement that would be acceptable before the study is attempted [3].

In summary, we found overall good inter-instrument reliability of the GT3X accelerometer across all planes. Our results also suggest that the addition of the X-axis and Z-axis does not provide further benefits to assess the movement in typical PA compared with 'classical' uni-axial (Y-axis) assessment of activity counts. The fact that our study involved only one subject may have influenced monitor placement results and thus represents a methodological limitation. Future research should be performed with several subjects, including both right- and left-handed people, to corroborate the influence of monitor placement.

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PAPER III:

“Actigraph GT3X: Validation and Determination of Physical Activity Intensity Cut Points”

Santos-Lozano A, Santín-Medeiros F, Cardon G, Torres-Luque G, Bailón R, Bergmeir C, Ruiz JR, Lucia A, Garatachea N. *The Actigraph GT3X Accelerometer: validation and determination of physical intensity cut points across age-groups. Int J Sports Med*. In press.

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Actigraph GT3X: Validation and Determination of Physical Activity Intensity Cut Points

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Key words
- activity monitor
- physical activity intensity
- energy expenditure

Abstract

The aims of this study were: to compare energy expenditure (EE) estimated from the existing GT3X accelerometer equations and EE measured with indirect calorimetry; to define new equations for EE estimation with the GT3X in youth, adults and older people; and to define GT3X vector magnitude (VM) cut points allowing to classify PA intensity in the aforementioned age-groups. The study comprised 31 youth, 31 adults and 35 older people. Participants wore the GT3X (setup: 1-s epoch) over their right hip during 6 conditions of 10-min duration each: resting, treadmill walking/running at 3, 5, 7, and 9 $km \cdot h^{-1}$, and repeated sit-stands (30 $times \cdot min^{-1}$). The GT3X proved to be a good tool to predict EE in youth and adults (able to discriminate between the aforementioned conditions), but not in the elderly. We defined the following equations: for all age-groups combined, EE (METs) $= 2.7406 + 0.00056 \cdot$ VM activity counts ($counts \cdot min^{-1}$) $- 0.008542 \cdot$ age (years) $- 0.01380 \cdot$ body mass (kg); for youth, METs $= 1.546618 + 0.000658 \cdot$ VM activity counts ($counts \cdot min^{-1}$); for adults, METs $= 2.8323 + 0.00054 \cdot$ VM activity counts ($counts \cdot min^{-1}$) $- 0.059123 \cdot$ body mass (kg) $+ 1.4410 \cdot$ gender (women = 1, men = 2); and for the elderly, METs $= 2.5878 + 0.00047 \cdot$ VM activity counts ($counts \cdot min^{-1}$) $- 0.6453 \cdot$ gender (women = 1, men = 2). Activity counts derived from the VM yielded a more accurate EE estimation than those derived from the Y-axis. The GT3X represents a step forward in triaxial technology estimating EE. However, age-specific equations must be used to ensure the correct use of this device.

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Introduction

Accelerometers allow objective assessment of physical activity (PA) in humans [9]. With the growing number of accelerometer models available in the market, there is an increased need to assess the accuracy of the new devices for PA and energy expenditure (EE) determination, i.e., using validation methods like doubly labeled water or indirect calorimetry [7]. For instance, several accelerometers models such as the CSA/7164, the GT1M, the Tritrac, the Caltrac or the Kenz Select have been validated with indirect calorimetry [1,3,6,10,19,24,27,33]. The validation of accelerometers with indirect calorimetry allows developing mathematical equation models to predict EE with these devices, as well as to define accelerometer-derived PA cut points [9,12,14,34]. The cut point method is commonly used to assess and classify free-living PA behavior in epidemiologic studies. However, cut points differ across accelerometer models and age ranges [11,17,18,25,39,40]. It is thus is necessary to develop specific cut points for each model and age range owing to the importance that PA levels have – as an exposure, main outcome or as confounder – in epidemiologic research [9].

In 2009, Actigraph launched a novel triaxial accelerometer, the so-called GT3X. Sasaki et al. [37] recently compared the GT1M and GT3X activity counts during treadmill walking/running activities. Activity counts obtained from the Y-axis were comparable between the 2 models, but not when obtained from the vector magnitude (VM, which is the vector summed value $\sqrt{X^2+Y^2+Z^2}$) Sasaki et al. [37] reported activity cut points from the VM in order to classify PA in young adults (mean age ~27 years). Although there are reports using the GT3X VM for EE determination [20,21,37], no previous study has assessed the accuracy of the GT3X or developed GT3X-specific equations for determining EE across different age-groups using the same protocol/activities, and the same methodology and statistical analysis.

The 3 main aims of this study were: (i) to compare EE estimated from the existing GT3X equations, and EE measured by indirect calorimetry in youth, adults and older people, and (ii) to improve the accuracy of the GT3X for predicting EE, by defining new equations in the same age-groups; and (iii) to develop GT3X VM cut points to classify PA intensity in the aforementioned age groups.

Methods

Subjects

The study was approved by the University's Human Ethics Committee, it was performed according to the declaration of Helsinki and it was in compliance with the Ethical Standards in Sport and Exercise Science Research [22]. All the subjects provided written consent to participate in the study. The subjects comprised:

(i) 31 youth (19 boys, 12 girls) aged 12–16 years (mean ± SD: 14.7 ± 1.0 years; weight: 59.6 ± 8.9 kg; height: 168.2 ± 6.6 cm; body fat, as estimated with bioelectrical impedance (Tanita BC 420SMA Portable Body Composition Monitor): 17.4 ±7.5 %);

(ii) 31 adults (16 men, 15 women) aged 40–55 years (47.1 ± 3.5 years; weight: 65.0 ± 16.7 kg; height: 168.0 ± 10.0 cm; body fat: 22.4 ± 6.1 %);

(iii) 35 older adults (13 men, 22 women) aged 65–80 years (71.9 ± 5.4 years; weight: 67.8 ± 17.5 kg; height: 160.9 ± 7.69 cm; body fat: 32.7 ± 5.8 %).

Our study design had a statistical power of 80 % to detect a difference between the group mean and a hypothetical mean of 0.65 METs with a significance level (alpha) of 0.05 (2-tailed).

Young people were recruited from the same high school, adults from the same university and from different fitness centers and older adults from different social centers. All subjects were living in the same city. Exclusion criteria were having musculoskeletal or cardiovascular diseases that could hinder PA. Participants were also excluded if they had any other contraindications to exercise or were taking medication altering metabolic rate. All participants completed the Physical Activity Readiness Questionnaire (PAR-Q), with a total of 3 older adults and 2 adults being excluded from the study because they answered yes to one or more questions.

Experimental procedure

3 GT3X units were updated with the 4.1.0 Firmware version. All units were initialized via a computer interface to collect data in 1-s epochs in the 3 axes. Each participant chose randomly one of the GT3X accelerometers, and the unit was positioned securely on the participants' right hip using an elastic belt. 2 researchers checked the position of the monitor before and after each condition (see below). The accelerometer test protocol consisted of 6 conditions (of 10-min duration each) interspersed with 5-min rest periods: (i) resting; (ii) treadmill (Quasar Med 4.0, h/p/cosmos, Nussdorf-Traunstein, Germany) walking at $3\,km \cdot h^{-1}$; (iii) treadmill walking at $5\,km \cdot h^{-1}$; (iv) treadmill walking or running at $7\,km \cdot h^{-1}$; (v) treadmill running at $9\,km \cdot h^{-1}$; and (vi) repeated sit-stands ($30\ times \cdot min^{-1}$). For safety reasons, older adults did not perform the treadmill bouts at $\geq 7\,km \cdot h^{-1}$. Oxygen uptake was measured 'breath-by-breath' continuously during each condition using indirect calorimetry (metabolic cart Oxycon Pro, Jaeger-Viasys Healthcare, Hoechberg, Germany). The metabolic cart was calibrated with a known gas mixture (16 % O_2 and 5 % CO_2) and volume prior to testing each subject [8]. One test had to be repeated seven days later due to an error in the security system of the treadmill. Occasional errant breaths (e.g. due to coughing, swallowing or talking) were deleted from the data set when exceeding 3 standard deviations of the mean, the latter being defined as the average of 2 following and 2 preceding sampling intervals [29].

Measurements

The Actigraph GT3X monitor device (Actigraph, Pensacola, FL, USA) is lightweight (27 g), compact (3.8 × 3.7 × 1.8 cm) and has a rechargeable lithium polymer battery [15]. It uses a solid-state tri-axial accelerometer to collect motion data on 3 axes: vertical (Y), horizontal right-left (X) and horizontal front-back axis (Z). The Actigraph output also includes the VM. The GT3X measures and records time-varying accelerations ranging in magnitude from ~0.05 to 2.5 Gs [15]. The accelerometer output is digitized by a 12-bit analog to digital convertor (ADC) at a rate of 30 Hz [15]. Once digitized, the signal passes through a digital filter that band-limits the accelerometer to the frequency range of 0.25–2.5 Hz [15]. Each sample is summed over an 'epoch' and the output of the Actigraph is given in 'counts'. The counts obtained in a given time period are linearly related to the intensity of the subject's PA during this period. There was no missing data due to errors attributable to accelerometers during the recording or downloading process.

Data analyses

Activity counts were obtained by averaging the activity counts of the four central minutes of each axis (X, Y, Z and VM). METs individually defined (VO_2 divided by measured Resting Metabolic Rate) from the indirect calorimetry were obtained in the same manner. To determine the axis effect on each activity, we used a 2-factor [condition (resting, walking at $3\,km \cdot h^{-1}$, walking at $5\,km \cdot h^{-1}$, walking or running at $7\,km \cdot h^{-1}$, running at $9\,km \cdot h^{-1}$, and repeated sit-stands), axis (X, Y, Z, and VM)] ANOVA test. When the assumptions of sphericity were violated, the Greenhouse Geisser correction factor was applied. A Bonferroni test was used post hoc in all pairwise comparisons when a significant result was found.

Study objective (i): to compare EE estimated from the existing GT3X equations, and EE measured by indirect calorimetry

We used a one-factor (EE) repeated-measures ANOVA to compare indirect calorimetry for each activity in each age-group and to analyze differences between activities. We also used a 3-factor [METs (obtained with indirect calorimetry, predicted from the GT3X), age-group (youth, adult, older) and condition (resting, walking at $3\,km \cdot h^{-1}$, walking at $5\,km \cdot h^{-1}$, walking or running at $7\,km \cdot h^{-1}$, running at $9\,km \cdot h^{-1}$, and repeated sit-stands)] ANOVA to compare GT3X-predicted METs and indirect calorimetry-determined METs in each age-group. If significant main effects were found, the Bonferroni test was used post hoc. We determined the degree of agreement (BIAS), standard deviation of BIAS (SD) and 95 % limits of agreement (LOA) between GT3X EE and indirect calorimetry EE using Bland & Altman plots [5].

The accuracy of previously proposed regression equations for EE estimation with the GT3X was determined by examining the BIAS, SD and LOA for each Bland-Altman plot. The equations we studied were: (i) the Work-energy Theorem [15], where EE (kcal·min^{-1}) = 0.000019 · activity counts (counts·min^{-1}) · body mass (kg); (ii) the combined equation [15] [Work-energy Theorem, where activity counts do not exceed 1952 counts·min^{-1}, and Freedson Equation, where activity counts exceed 1952 counts·min^{-1} (Freedson Equation: EE (kcal·min^{-1}) = 0.00094 activity counts (counts·min^{-1}) + 0.1346 body mass (kg) − 7.37418)]; (iii) and the equation reported by Sasaki et al. [37], where EE (METs) = 0.000863 (VM) + 0.668876.

Study objective (ii) to define new equations to estimate EE with the GT3X in youth, adults and older people

To determine the new equations in each age-group, we used linear regression analysis to predict METs from VM GT3X counts·min^{-1}. The accuracy of the new proposed equations was examined by calculating the BIAS, SD and LOA for each Bland-Altman plot. A leave-one-out cross validation was performed for assessing if the equations could be generalized to an independent data set. Finally, the association between the difference and the magnitude of the measurement (i.e., heteroscedasticity) was examined by regression analysis, entering the difference between the EE measured and the EE estimated using the EE (METs) of the proposed new equation as dependent variable and the averaged value [(indirect calorimetry + estimated)/2] as independent variable [2].

Study objective (iii) GT3X VM cut points

PA intensity level is commonly defined according to MET [23] (moderate intensity: 3.00–5.99 METs; vigorous intensity: 6.00–8.99 METs; very vigorous intensity: ≥ 9 METs). The mathematical model used to build the equation to estimate MET from VM activity counts was an ANN. An ANN is a mathematical model that emulates some of the observed properties of biological nervous system and draw on the analogies of adaptive biological learning. VM activity counts cut points were given according to the MET for PA intensity level classification [23]. 4 ANN were defined, one for each age-group and one for all participants. The first layer of each ANN (the input layer) corresponds to the independent variable (activity counts from VM), while the third layer (the output layer) corresponds to the dependent variable score (METs). The intermediate layer, which is a hidden layer (3 hidden layers in each ANN) consists of all possible connections between the input and the output layer. The activation function for the hidden and output nodes was the logistic function, and function computed by the hidden unit was lineal. In order to obtain the synaptic weights of the ANN, the back-propagation algorithm was used [36], and the values for the algorithm parameters were 0.2 for the learning rate and 0.5 for the momentum term. The training of the network is stopped when the SSE falls below 0.00001 [35].

Sensitivity, specificity and area under the receiver operating characteristic curve (ROC-AUC value) [43] were also calculated to evaluate the ability of the new cut points to accurately classify the PA intensity level.

Statistical analyses were performed using PASW (Predictive Analytics SoftWare, v. 18.0 SPSS Inc., Chicago, IL, USA). Data is presented as mean ± standard deviation (SD), unless state otherwise. Significance level was set at $P \leq 0.05$. ANN-models were defined using the RSNNS software [4] and the study power of our design was calculated by the StatMate software, version 2.0 (GraphPad, San Diego, USA).

Results

Activity counts per axis increased with the intensity of activities (**Fig. 1**) as well as EE values (METs) obtained with indirect calorimetry (**Fig. 2**). Results are presented in METs to make comparisons across studies easier [42].

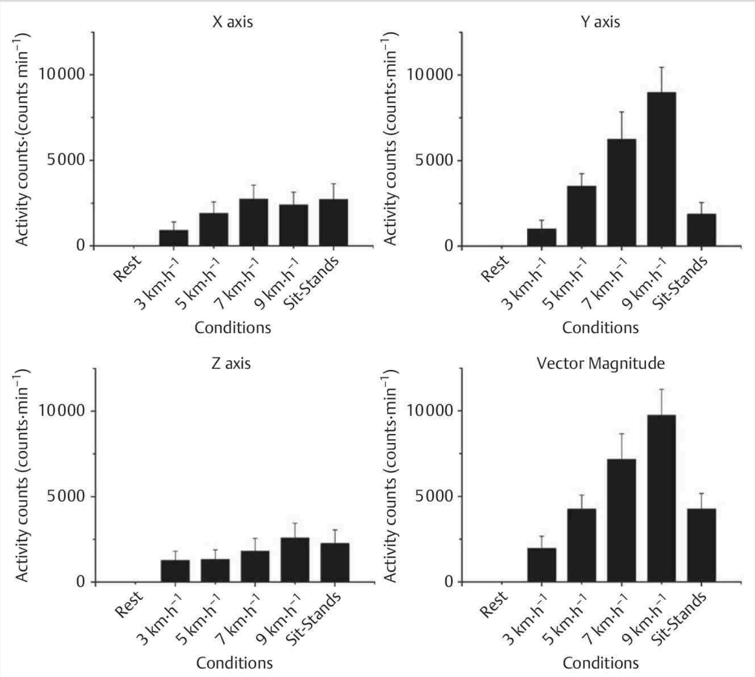

Fig. 1 Activity counts (counts·min^{-1}) (mean ± standard deviation) per axis and activities for all participants.

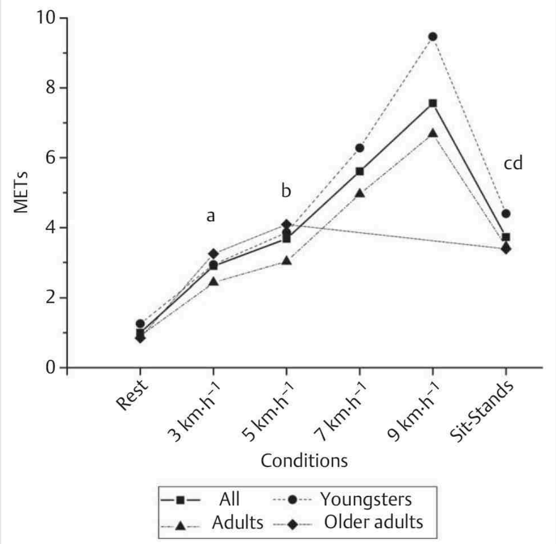

Fig. 2 Energy expenditure (in METs) determined by indirect calorimetry by activity for each age-group. [a]No significant different from 3 km·h^{-1}, same gender and age group, $P>0.05$. [b]No significant different from 5 km·h^{-1}, same gender and age group, $P>0.05$. [c]No significant different from sit-stand, same gender and age group, $P>0.05$.

Comparison between EE estimated from the existing GT3X equations and EE measured with indirect calorimetry

EE values predicted from the equation provided by the Actigraph manual [15] and from the equation previously reported by Sasaki et al. [37] were compared with EE values obtained with indirect calorimetry. The results of BIAS (indirect calorimetry – EE predicted) and LOA are shown in **Table 1**. Following the criterion used by Crouter et al. [13], the less accurate equation was the work-energy theorem equation for adults using VM activity counts output (BIAS: −1.856; SD: 2.848; LOA: −7.437 to 3.725), whereas the most accurate equation was the Combined Equation in children using activity counts output from VM (BIAS = −0.053; SD = 1.776; LOA = −3.534 to −3.428).

Definition of new equations to estimate EE in youth, adults and older adults

The VM yielded a more accurate value of activity counts for EE prediction than the Y-axis. The best possible equations for VM and Y are shown in **Table 2**. The Bland and Altman plots for the VM are shown in **Fig. 3** and their BIAS (indirect calorimetry – EE predicted) are shown in **Table 1**.

The leave-one-out cross validation analysis confirmed the coefficients of each variable and the constant in each age group. The mean of the error and the SD of the error were −1.758 and 1.980 in all groups together, −1.571 and 1.864 in youth, −2.152 and 1.97 in adults, and 0.011 and 1.114 in older people respectively.

Table 1 BIAS, standard deviation of the BIAS (SD) and 95% limits of agreement (LOA) for each age-group, in previously published and proposed equations.

Group	Axis	Author	Units	BIAS	SD	LOA	
All (n = 97; 49 women)	Y	Work-energy theorem	kcal·min^{-1}	0.4007	2.409	−4.321	5.122
		Combined	kcal·min^{-1}	0.5390	2.226	−3.824	4.902
	VM	Work-energy theorem	kcal·min^{-1}	0.8193	2.523	−5.764	4.125
		Combined	kcal·min^{-1}	−0.6365	2.342	−5.227	3.955
		Sasaki et al.	METs	−0.4115	1.695	−3.734	2.911
		New proposed	METs	−0.005955	1.396	−2.742	2.730
Youth (n = 31; 12 girls)	Y	Work-energy theorem	kcal·min^{-1}	0.5621	2.026	−3.409	4.533
		Combined	kcal·min^{-1}	0.8724	1.779	−2.614	4.358
	VM	Work-energy theorem	kcal·min^{-1}	−0.4481	2.008	−4.383	3.487
		Combined	kcal·min^{-1}	−0.05281	1.776	−3.534	3.428
		Sasaki et al.	METs	0.1967	3.340	−6.349	6.742
		Newly proposed	METs	−0.0012	1.486	−2.914	2.911
Adults (n = 31; 15 women)	Y	Work-energy theorem	kcal·min^{-1}	−0.6162	2.779	−6.063	4.831
		Combined	kcal·min^{-1}	−0.4281	2.437	−5.205	4.349
	VM	Work-energy theorem	kcal·min^{-1}	−1.856	2.848	−7.437	3.725
		Combined	kcal·min^{-1}	−1.547	2.435	−6.319	3.225
		Sasaki et al.	METs	−0.7283	3.641	−7.865	6.409
		Newly proposed	METs	−0.01050	1.199	−2.360	2.339
Older adults (n = 35; 22 women)	Y	Work-energy theorem	kcal·min^{-1}	1.530	1.679	−1.760	4.820
		Combined	kcal·min^{-1}	1.388	1.971	−2.476	5.251
	VM	Work-energy theorem	kcal·min^{-1}	0.07354	2.168	−4.175	4.323
		Combined	kcal·min^{-1}	−0.1753	2.485	−5.046	4.686
		Sasaki et al.	METs	−0.7590	2.836	−6.318	4.800
		Newly proposed	METs	0.004506	1.132	−2.215	2.224

Table 2 New equations proposed.

Group	Axis	Equation	R	R^2	SEE (±)	RMSE
All participants	Y	*METs = 3.14153 + 0.00057 · Y-axis AC – 0.01380 · BM – 0.00606 · A*	0.78	0.60	1.45	1.45
(n = 97; 49 women)	VM	*METs = 2.7406 + 0.00056 · VM AC – 0.008542 · A – 0.01380 · BM*	0.78	0.66	1.40	1.40
Youth	Y	*METs = 2.118079 + 0.000662 · Y-axis AC*	0.81	0.65	1.56	1.55
(n = 31;12 girls)	VM	*METs = 1.546618 + 0.000658 · VM AC*	0.83	0.68	1.49	1.49
Adults	Y	*METs (kcal · min^{-1}) = 3.4002 + 0.00053 · Y-axis AC – 0.05564 · BM + 1.2789 · G*	0.82	0.67	1.28	1.27
(n = 31;15 women)	VM	*METs = 2.8323 + 0.00054 · VM AC – 0.05912 · BM + 1.4410 · G*	0.84	0.71	1.21	1.20
Older adults	Y	*METs (kcal · min^{-1}) = 2.8867 + 0.00067 · Y-axis AC– 0.6807 · G*	0.50	0.36	1.18	1.17
(n = 35; 22 women)	VM	*METs = 2.5878 + 0.00047 · VM AC – 0.6453 · G*	0.64	0.41	1.14	1.13

Activity counts (AC): counts · min^{-1}; Age (A): years; Body mass (BM): Kg; Gender (G): women 1; man 2; R: correlation coefficient; R^2: coefficient of correlation; SEE: standard error of the estimation; RMSE: root mean sum of squared errors

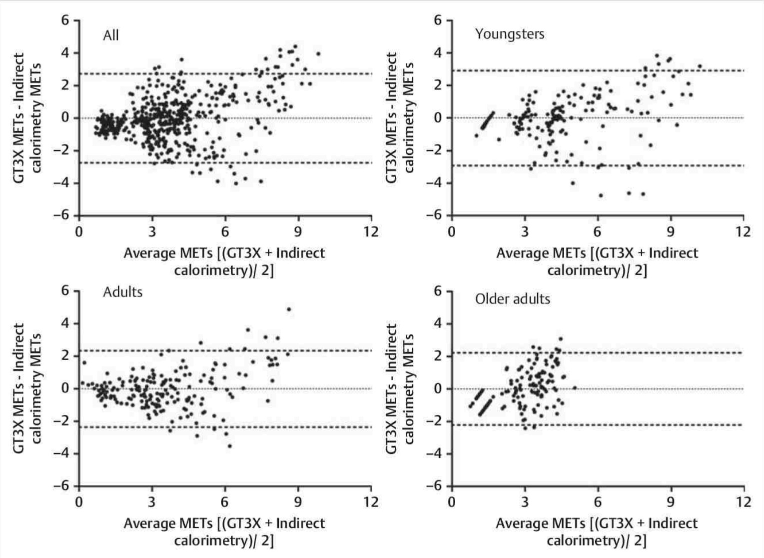

Fig. 3 Bland and Altman Plots in each group (energy expenditure (EE, in METs) determined with indirect calorimetry – EE (METs) predicted with GT3X).

For all age groups, the heteroscedasticity analysis showed a significant positive association (R = 0.528, *P* = 0.01) between the difference and the average of the EE measured with indirect calorimetry and the GT3X-estimated EE using the new proposed equation. We also found a significant positive association in youth (R = 0.558, *P* = 0.01) and adults (R = 0.536, *P* = 0.01), but not in older adults (R = 0.043, *P* = 0.615). Differences between EE predicted with the GT3X-new proposed equation and EE determined with indirect calorimetry are shown in **Fig. 4**.

GT3X VM cut points to classify PA intensity across age-groups

Activity cut points were determined from VM activity counts in each age-group using ANN model and are presented in **Table 3**. Values for youth were the lowest, whereas values were higher for adults than for older people in order to obtain the same METs intensity.

Values of the area under the ROC curve, sensitivity and specificity for the proposed cut points are shown in **Table 4**.

Discussion

The main study findings were as follows. First, the combined equation for MET estimation [15] (work-energy theorem, where counts per minute not exceed 1952 and Freedson equation, where counts exceed 1952 (kcal · min^{-1} = 0.00094 · *activity counts (counts · min^{-1})*+0.1346·*body mass (kg)*−7.37418) yielded better results than the rest of previous available equations. Secondly, we defined a new, more accurate equation for each age-group: for all age-groups combined, *METs = 2.7406 + 0.00056 · VM activity counts (counts · min^{-1}) – 0.008542 · age (years) – 0.01380 · body mass (kg)*; for youth, *METs = 1.546618 + 0.000658 · VM activity counts (counts · min^{-1})*; for adults, *METs = 2.8323 + 0.00054 · VM activity counts (counts · min^{-1}) – 0.059123 · body mass (kg) + 1.4410 · gender (women = 1, men = 2)*; and for older people, *METs = 2.5878 + 0.00047 · VM activity counts (counts · min^{-1}) − 0.6453 · gender (women = 1, men = 2)*. Thirdly, we also defined new cut points in each group (**Table 3**). When evaluating the GT3X in the treadmill, we found that activity counts increased as walking/running speed increased, with the GT3X being able to differentiate among the different activities (**Fig. 1**). Sasaki et al. [37] obtained similar activity counts with the GT3X and

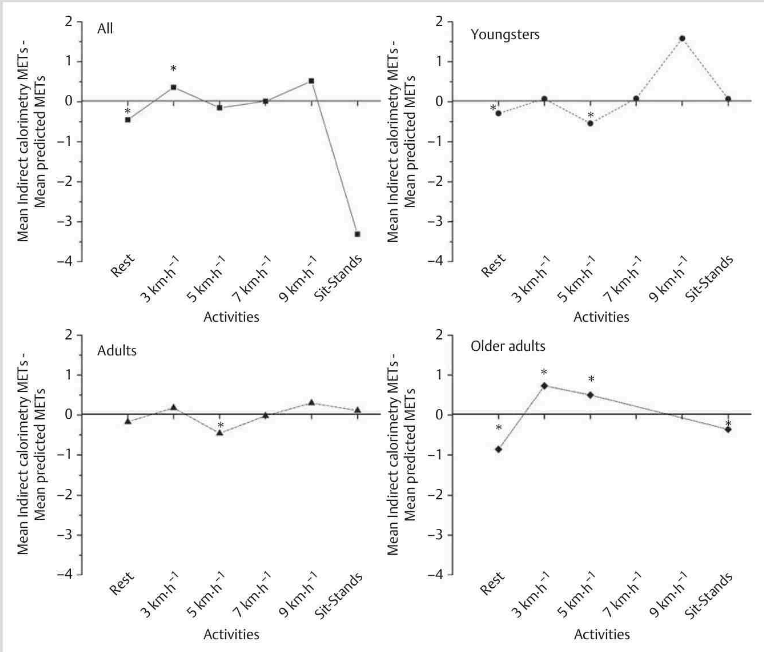

Fig. 4 Energy expenditure (EE, in METs) from indirect calorimetry vs. EE predicted with the GT3X for each age-group. *Significantly different from indirect calorimetry vs. predicted, same activity and age-group, $P<0.05$.

Table 3 Vector magnitude cut points for each age-group.

MET	All	Youth	Adults	Older adults
3	1480	2114	3208	2751
6	8505	6548	8565	9359
9	10500	11490	11593	–

Equation used to calculate cut points for:

All age-groups:

METs = ((1/(1 + EXP(9.18694*((VM − 4027.474318)/3153.286042) + 12.9723))* − 3.05383 + 1/(1 + EXP(1.8487*(VM-4027.474318) + 2.55011))* −1.19096 + 1/(1 + EXP(3.84729*(VM − 4027.474318) + 4.11932))*1.24936))*2.303724 + 3.733038

BIAS = −0.2432; SD = 1.404; 95 % limit of agreement (LOA) = −2.995–2.509

Youth:

METs = ((1/(1 + EXP(0.16215*((VM − 2507.143359)/1971.403158) + 2.17929))* 2.40308 + 1/(1 + EXP(0.16208*((VM − 2507.143359)/1971.403158) + 2.18143))* 2.40712 + 1/(1 + EXP(9.87464*((VM − 2507.143359)/1971.403158) + 11.08109))* −2.49037)2.221964) + 3.57993 BIAS = −0.1740; SD = 1.433; LOA = −2.983 to 2.635

Adults:

METs = ((1/(1 + EXP(−2.90002*(VM − 4648.8881)/3350.015592) + 2.8147))* 1.75949 + 1/(1 + EXP(1.20619*(VM − 4648.8881)/3350.015592) + 2.53866))* −1.79643 + 1/(1 + EXP(2.61969*(VM − 4648.8881)/3350.015592) + 4.57437))* −2.60096)*2.221964) + 3.57993BIAS = 0.01220; SD = 1.307; LOA = −2.550 to 2.575

Older adults:

METs = ((1/(1 + EXP(−4.6483*(VM − 4590.980124)/3311.158625) + 2.70339))* 1.11173 + 1/(1 + EXP(0.37229*(VM − 4590.980124)/3311.158625) + 3.44165))* 0.53061 + 1/(1 + EXP(2.3635*(VM − 4590.980124)/3311.158625) + 2.52525))* −1.93496)*2.636543) + 4.566316BIAS = −0.0716; SD = 0.8640; LOA = −1.765 to 1.622

Where METs is metabolic equivalents, and VM is vector magnitude

the GT1M, i.e. for the Y-axis, ~3000 counts·min^{-1} at 4.8 km·h^{-1}, ~4500 counts·min^{-1} at 6.4 km·h^{-1} and ~9500 counts·min^{-1} at 9.7 km·h^{-1}; and for the VM, ~4000 counts·min^{-1} at 4.8 km·h^{-1}, ~6000 counts·min^{-1} at 6.4 km·h^{-1}, and ~10000 counts·min^{-1} at 9.7 km·h^{-1}.

No studies are available addressing the accuracy of the Actilife equation for EE estimation with the GT3X, or potential differences in activity counts between the VM and the Y-axis with this accelerometer. Our results showed that the equations published in the Actilife manual do not appear sufficiently accurate for EE estimation. The most accurate values for EE prediction were obtained with the combined equation for activity counts in the Y-axis. In the older group, the best values corresponded to the work-energy theorem equation in the Y-axis. For the adult age-group, the best result corresponded to activity counts obtained with the combined equation in the Y-axis. However, among the young subjects, the best values for activity counts corresponded to the VM and the combined equation. We also tested the equation proposed by Sasaki et al. [37] using activity counts from the VM. However, the results were more accurate for all age-groups combined than for specific age-groups. Upon comparing our results with those of previous studies [19,30–32,41], it appeared necessary to develop a new equation for EE prediction, because the available equations are not sufficiently accurate.

In order to determine the best equation and axis to predict EE, we used the Bland-Altman approach [13] in each age-group. We found that the new equations we proposed are more accurate for EE estimation than the equation provided in the Actigraph manual or the one previously used by Sasaki et al. [37]. Further, in treadmill activities and in the sit-stand test, activity counts obtained from VM yielded a slightly more accurate prediction of EE than those obtained from the Y-axis. In contrast, Howe et al. [26] found that for the RT3 accelerometer the VM did not yield more accurate values of activity counts than the Y-axis. The results of the present study indicate that the GT3X provides an accurate estimation of EE during treadmill walking, except in older adults. Likewise, the new equations for adults and youth were more accurate for the entire group with the exception of the elderly. This could be due to the gaps in the age ranges of our sample. Fehling et al. [16] found that in older people the Caltrac accelerometer overestimated the EE of treadmill walking, whereas the Tritrac accelerometer underestimated the EE of this activity. Recent work by Strath et al. [42] also highlighted the

Table 4 Values of the area under the ROC curve, sensitivity (%) and specificity (%) for the proposed cut points per intensity and group.

		Light	Moderate	Vigorous	Very vigorous
All	Area	0.8	0.7	0.6	0.6
	Sensitivity (%)	89.9	56.6	24.4	21.4
	Specificity (%)	27.1	21.2	24.4	10.6
Youth	Area	0.8	0.7	0.7	0.6
	Sensitivity (%)	80.9	66.7	49.1	43
	Specificity (%)	18.1	22.3	19	18.6
Adults	Area	0.8	0.6	0.7	0.6
	Sensitivity (%)	84.6	52.2	46	43
	Specificity (%)	28.1	22.3	20	21
Older adults	Area	0.7	0.7		
	Sensitivity (%)	68.5	72.5		
	Specificity (%)	27.5	31.5		

(Area under the ROC curve; sensitivity (%); specificity(%))

lack of accurate equations for accelerometry-derived EE estimation in older adults.

Previous research has shown comparable activity count values in the Y-axis when using the GT1M or the GT3X accelerometer [37]. However, we demonstrated that for the GT3X accelerometer, the VM allowed for a more accurate EE prediction than the Y-axis. As such, it is necessary to identify VM cut points in different populations. With regards to this, Sasaki et al. [37] established the following VM cut points for young adults (26.9 ± 7.7 years): for moderate intensity activities (3–5.99 METs) 2 690 to 6 166 counts·min^{-1}; for hard activities (6–8.99 METs) 6 167 to 9 642 counts·min^{-1}; and for very hard activities (≥9 METS) > 9 642 counts·min^{-1}. The authors included the mean differences between actual and predicted METs (−0.3, −0.4, and 0.7 METs at 4.8, 6.4 and 9.7 km·h^{-1}, respectively), yet did not describe the values of the SD of BIAS. For the 3 age-groups we studied here, the mean differences were lower than those reported by Sasaki et al. [37], which could be explained by the fact that these authors assessed activity counts and METs only at three activities (4.8, 6.4 and 9.7 km·h^{-1}), whereas here we used six different activities or 'conditions' (including resting). In addition, Sasaki et al. established the cut-points value using linear regression. Another explanation could lie in the difference in the monitor firmware, as here we used the 4.1.0 firmware update, whereas Sasaki et al. used the firmware 1.3.0.

A main limitation of our design is that all tested activities (treadmill walking/running and sit-stands) were performed in a laboratory setting instead of being performed in free-living conditions. With regard to this situation, futures studies should assess the generalizability of laboratory-derived equations to free life settings, following recent recommendations by Staudenmater et al. [38]. Furthermore, other potential confounders, such as fitness level, adiposity and maturational status were not considered. Future research should cross-validate in different population cohorts the new equations we defined as well as improve the accuracy of the equations by controlling analyses for the aforementioned confounders. On the other hand, we believe our design has several strengths. We studied a relatively large sampling of subjects and 3 different age-groups. We also provided new equations to predict EE and new cut points for the use of VM activity counts in the different age-groups. Moreover, this is the first study comparing the accuracy of the VM vs. the Y-axis for EE prediction with the GT3X accelerometer.

To our knowledge this is the first study to (i) define cut points values by an ANN, or (ii) calculate AUC, sensitivity and specificity for assessing the accuracy of the cut points being defined. The main limitation of the ANN is its complexity and its "black box" nature. The complexity of the ANN-equation may become rather inconvenient when applied in the field. Therefore, ANN was only used to define cut points and not for the new equations used to determine EE. The sensitivity and the specificity analysis revealed that the cut points were able to sufficiently distinguish the true positives, but not the true negatives. The latter finding was to be expected, because the monitor registers acceleration, and some PA patterns could be associated with large accelerations without an increment of the EE. However, in the event of an increment of EE, activity counts are always increased [28].

In conclusion, the GT3X appears to overall be an accurate tool for EE prediction, which proved sufficiently sensitive to discriminate between different intensities of PA, at least for activities performed in a laboratory setting. On the other hand, in order to use accurate GT3X VM cut points for EE estimation, these cut points have to be age-specific. Compared to more traditional uniaxial or biaxial devices, a technical step forward of the GT3X triaxial accelerometer for EE estimation during human PA performed in all axes is the higher accuracy of the VM vs. the Y-axis. However, more accurate equations for EE estimation are needed in older people.

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▼

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PAPER IV:

"Tendencias actuales de la acelerometría para la cuantificación de la actividad física"

Santos-Lozano A, Garatachea N. *Tendencias actuales de la acelerometría para la cuantificación de la actividad física*. *Current trends of accelerometry to assess physical activity*. RICCAFD. 2012 Ago; 1 (1): 24-32.

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TENDENCIAS ACTUALES DE LA ACELEROMETRÍA PARA LA CUANTIFICACIÓN DE LA ACTIVIDAD FÍSICA

CURRENT TRENDS OF ACCELEROMETRY TO ASSESS PHYSICAL ACTIVITY

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PALABRAS CLAVE:
Actividad Física, Acelerómetro, Acelerometría, Monitores de Actividad

RESUMEN

Evaluar la actividad física de forma precisa y fiable sigue siendo un importante reto para los epidemiólogos, científicos, médicos, especialistas en ejercicio e investigadores del comportamiento. Para ello, actualmente, los acelerómetros son dispositivos ampliamente utilizados en investigación científica. En el presente artículo se pretende dar muestra de cuál es la situación actual del uso de la acelerometría para cuantificar niveles de actividad física. Así como sus limitaciones y perspectivas de futuro con el fin de contribuir a su mejor uso.

KEY WORDS:
Physical Activity, Accelerometers, Accelerometry, Activity Monitors.

ABSTRACT

To assess precisely and reliability the Physical Activity is still a challenger to the epidemiologist, scientific, medicals, exercise specialists and behavioural researchers. Nowadays, the accelerometers are monitors activity broadly used in scientific research. The present work has as an aim to show the real situation of the accelerometry to quantify Physical Activity Levels, as well as, their limitations and future directions in order to promote a better use of this technology.

INTRODUCCIÓN

El deseo de lograr comprender mejor la relación entre actividad física y salud, así como poder explicar el drástico aumento en la prevalencia de sobrepeso y obesidad en jóvenes y adultos, ha centrado la atención en la necesidad de mejorar las herramientas utilizadas para cuantificar los niveles de actividad física.

El desarrollo tecnológico ha permitido generar instrumentos fáciles de utilizar y que, de una manera objetiva, valoran el nivel de actividad física. Por ejemplo, en la década de los noventa del pasado siglo XX, el monitor de frecuencia cardíaca fue ampliamente utilizado, siendo el método de elección preferido por muchos investigadores (1) para medir la intensidad de la actividad física por medio de los latidos por minuto del corazón. Sin embargo, se desarrolló el empleo de los podómetros, que miden la actividad física de forma también objetiva contabilizando el número de pasos por día, pero carecen de la posibilidad de cuantificar su intensidad. Por eso, en los últimos años se ha incrementado la popularidad y el empleo de los acelerómetros como herramientas objetivas de cuantificación de la actividad física en distintas poblaciones (2,3,4), proporcionando información relativa sobre la intensidad, la frecuencia y la duración de la actividad física desarrollada de la persona que lleva el monitor.

En este sentido, se pueden realizar algunas reflexiones relativas a los acelerómetros para contextualizar la fase investigadora en la que se encuentran, las futuras direcciones que pueden tomar, conocer sus limitaciones y contribuir a su mejor uso.

ESTADO ACTUAL DE LA INVESTIGACIÓN E INVESTIGADORES MÁS RELEVANTES

En la década de los años 90, la acelerometría estaba todavía considerada en fase de desarrollo. En 1999 se llevó a cabo en el prestigioso Instituto Cooper el congreso "Measurement of Physical Activity", donde se facilitaron a la comunidad científica algunas conclusiones y recomendaciones futuras sobre el empleo de los acelerómetros. Desde entonces, los investigadores han dedicado grandes esfuerzos para responder a la necesidad de mejorar este campo con los avances tecnológicos y las nuevas aplicaciones de tecnologías existentes y emergentes. La literatura científica publicada proporciona una demostración de su importancia a partir de esta fecha. En la figura 1 se puede observar la tendencia ascendente en el número de publicaciones de artículos científicos que tratan sobre acelerometría desde entonces. Los datos fueron obtenidos mediante búsquedas en la base de datos bibliográfica Medline entre los artículos originales de investigación o revisiones que incluían los términos "acelerometer", "activity monitor", "physical activity", "sport" y/o "exercise" en el título, palabras clave o resumen.

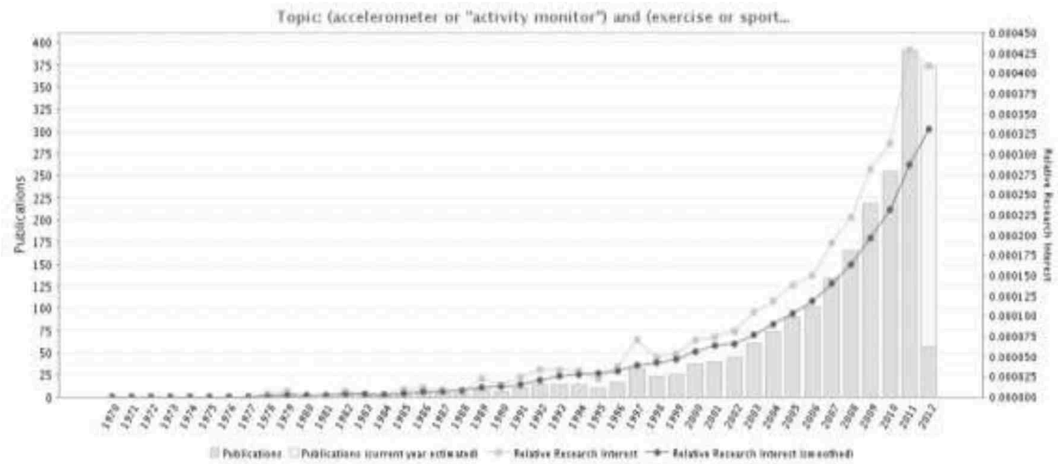

Figura 1. Evolución de las publicaciones a lo largo del tiempo

En la figura 2 se muestran el número de publicaciones relacionadas con acelerometría en revistas internacionales y con factor de impacto, siendo *"Medicine and Science in Sport and Exercise"* la revista en las que más se han publicado.

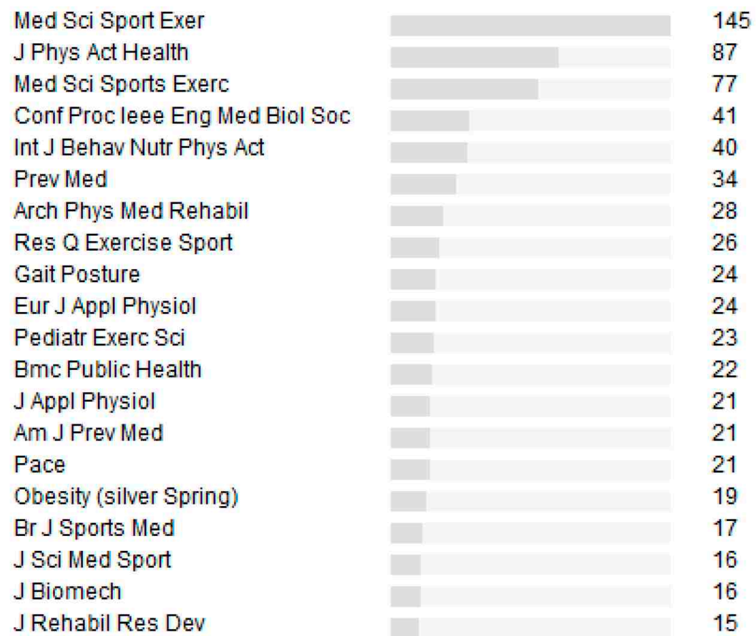

Figura 2. Ranking de revistas que han publicado sobre acelerometría

Por último, en la figura 3 se puede observar los autores que más han publicado en revistas de prestigioso nivel sobre esta temática.

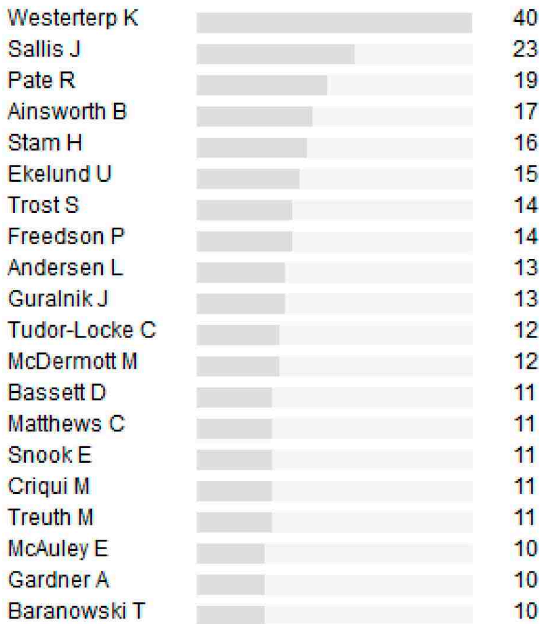

Figura 3. Lista de los autores que más han publicado en acelerometría

LIMITACIONES DE LOS ACTUALES MONITORES

A pesar de las conocidas ventajas de los acelerómetros para medir los niveles de actividad física y estimar gasto energético, es necesario que los investigadores conozcan sus limitaciones.

- Las unidades que los acelerómetros proporcionan como indicador de movimiento (counts) no son equivalentes entre marcas y, muchas veces, tampoco entre monitores de la misma. Además, los algoritmos patentados para estimar el gasto calórico (5) son únicos para cada monitor. Esto reduce en muchas ocasiones la posibilidad de comparar entre distintos modelos y marcas existentes en el mercado.

- Cada marca de acelerómetro posee su propio software, que se necesita para iniciar, configurar y descargar el registro de cada dispositivo en cuestión.

- El tiempo invertido por el personal investigador en procesar y analizar los datos es alto, siendo mayor en sensores múltiples y estudios epidemiológicos (6).

- Se debe entrenar a los usuarios para utilizar el dispositivo de monitorización prestando cuidadosa atención a su colocación (7).

- Es necesario definir el protocolo y la configuración del acelerómetro teniendo en cuenta el tiempo de almacenamiento de la información (epoch), horas de registro diario, número de días y días de la semana (entre semana o fin de semana) en los que se va a analizar el nivel de actividad física (6).

- Una de las principales limitaciones estriba en que la mayoría de los acelerómetros piezoeléctricos son sólo fiables para detectar eventos dinámicos, pudiendo ocurrir un fenómeno denominado *leakage*. Este se produce cuando el cambio inicial en la carga en el elemento piezoeléctrico del monitor se disipa en el tiempo, incluso si la carga estática que causó el cambio inicial está todavía presente (misma velocidad, aceleración diferente) (8). La frecuencia con la cual se produce este fenómeno va a depender de la constante tiempo, una propiedad física del material piezoeléctrico.

- Así, los acelerómetros piezoeléctricos presentan una incapacidad para detectar el componente estático de la aceleración, esto significa que no son capaces de medir los ángulos con respecto a la gravedad de la superficie y la postura (de pie versus sentado). Sin embargo, un novedoso monitor denominado Activpal, que se coloca en el muslo, tiene un inclinómetro que detecta la postura de la persona (de pie estático, sentado y/o descansando o en comportamiento no sedentario). Además, otros monitores consistentes en múltiples sensores proporcionan una definición más precisa de la posición, pero el análisis de los datos es más complicado que el uso de una sola unidad.

- La exactitud y precisión de cada dispositivo depende de una buena calibración de la unidad, lo que reduce la variabilidad intermonitores. Sin embargo, esta unidad de calibración no es la misma con el paso del tiempo, con lo que se necesita calibración periódica. Hay que tener en cuenta que existe una tecnología actual, por medio de un chip integrado, donde la calibración es menos necesaria. Otros aspectos como las caídas, altas y bajas temperaturas y un uso prolongado en el tiempo son factores que disminuyen la calibración correcta del acelerómetro.

- Una de las limitaciones más destacadas de los acelerómetros es la imposibilidad de captar algunos tipos de actividad física diaria, fundamentalmente relacionada con los movimientos de las extremidades superiores del cuerpo. Por ejemplo, no es posible detectar movimientos de los brazos mientras se permanece sentado con monitores simples, así como saber si el sujeto monta en bicicleta o levanta de pesas.

- A su vez, tanto los sensores simples como múltiples, son ineficaces en la estimación del consumo de energía en determinadas situaciones, como por ejemplo caminar o correr en pendiente o llevar una carga.

- El elevado precio de los monitores (<150€) puede considerarse una limitación.

Futuras direcciones

Actualmente existe una tecnología emergente, fruto de la necesidad de mejora. En este sentido, son varios los laboratorios de investigación y empresas que han puesto diversas estrategias en marcha: a) Utilizar monitores con múltiples sensores que se colocan en diferentes partes del cuerpo (tobillos, cintura, muñecas…) y, b) Combinar el acelerómetro con otro sensor fisiológico (frecuencia cardiaca, temperatura…) integrado en un único dispositivo.

Chen y Basset (8), en una interesante revisión, concluyeron que los futuros monitores de acelerometría deberían estar diseñados con el fin de mejorar significativamente su capacidad de predecir el gasto energético. Además, con el fin de ser lo suficientemente portátiles y fuertes para su aplicación en la vida diaria deben seguir dos criterios fundamentales: 1) Deben ser compactos y no tener ningún, o la menor cantidad posible de cables y, 2) Deben poseer una capacidad suficiente de procesamiento de datos y de almacenamiento durante un periodo extenso de tiempo.

Acelerómetros con múltiples sensores

Esta clase de acelerómetros tienen la capacidad de detectar cambios posturales y movimientos de baja intensidad, principal limitación de los acelerómetros que se portan en la cintura. La aplicación de este tipo de dispositivos se ha realizado principalmente en laboratorios de investigación y están orientados a la rehabilitación de pacientes con amputación de una pierna, cirugía de espalda o insuficiencia cardiaca crónica entre otros trastornos físicos.

Recientemente, ha sido lanzado al mercado un dispositivo inteligente para la estimación de gasto de energía y actividad llamado IDEEA, (IDEEA, MiniSun LLC, Fresno, CA), un nuevo microprocesador portátil de actividad física. El IDEEA fue diseñado con el fin registrar los movimientos complejos de la actividad física diaria empleando sensores piezoeléctricos en el pecho, muslos y pies. Utiliza sensores de movimiento de pequeño tamaño, con un peso menor de un gramo, que se colocan con cinta hipoalérgica en cinco localizaciones: el pecho (esternón superior), la mitad del muslo en ambas piernas y ambos pies. La escala de los sensores es de ± 2 G. Además lleva una minicomputadora (59 g de peso) en la cintura donde a la que se conectan tres cables delgados y flexibles. De esta manera es capaz de diferenciar entre posturas sedentarias y movimientos activos.

La validación clínica de IDEEA ha sido publicada en 2010 por el New York Obesity Research Center (9), Universidad de Columbia sobre Investigación en obesidad. El IDEEA tiene las siguientes funciones principales:

- Graba y reproduce los cambios de movimiento y de postura del cuerpo sobre una base de 24h, almacenando decenas de millones de datos para futuros análisis.

- Identifica más de 40 tipos de actividad física, incluyendo estar acostado, estar sentado, caminar, subir escaleras, correr y saltar.

- Proporciona grabaciones exactas de la aparición, duración y frecuencia de la actividad física y otros acontecimientos importantes del día; llevando a cabo un análisis detallado de la actividad física y de los componentes de gasto de energía en categorías, distribuyéndolas en un período determinado de tiempo.

- Calcula la cantidad y la intensidad de la actividad física (por ejemplo, la velocidad de la marcha) utilizando técnicas tales como la inteligencia artificial y redes neuronales, proporcionando los resultados más precisos jamás reportados para un dispositivo portátil.

- Proporciona resultados como la cantidad de trabajo mecánico y la estimación del gasto energético en un periodo determinado. Estos datos son fundamentales para el control del peso y la obesidad, los programas de capacitación fitness y/o salud y para centros de rehabilitación y evaluación funcional.

Dispositivos que combinan la acelerometría con otras mediciones fisiológicas

Muchos investigadores también han tratado de combinar la frecuencia cardíaca con acelerómetros (en monitores separados) mostrando mejoras significativas en la precisión de la predicción. Los detalles de los métodos que combinan la frecuencia cardíaca y la acelerometría han sido revisados por Strath et al. (10) y Brage et al. (11). La combinación de aceleración con la frecuencia cardíaca y otras mediciones en una sola unidad podría simplificar los procesos de aplicación, descarga de datos y sincronización. Con este nuevo enfoque, actualmente destacan dos dispositivos disponibles para los investigadores: el Actiheart y el SenserWear.

El Actiheart (Mini Mitter Co., Inc.) es un dispositivo que ha integrado un acelerómetro (uniaxial) con una señal de electrocardiografía, detectando simultáneamente la frecuencia cardiaca y el movimiento del cuerpo. Se ha demostrado que la Actiheart predice el gasto energético a partir de un modelo de acelerometría y frecuencia cardiaca significativamente más preciso que si se emplea cualquiera de los dos parámetros de manera aislada (11).

Por otro lado, el brazalete SenseWear (BodyMedia Inc., Pittsburgh, PA) es otro monitor disponible recientemente en el mercado y que está diseñado para que se lleve puesto en la parte superior del brazo. Los sensores internos de los que dispone incluyen un sensor de acelerometría, un sensor de flujo térmico, un sensor galvánico que registra la respuesta de la piel, un sensor de temperatura de la piel y un sensor de proximidad de la temperatura ambiente del cuerpo. El acelerómetro en el brazalete es de dos ejes que utiliza un dispositivo sensor microelectromecánico que mide el movimiento. El software del fabricante calcula el gasto de energía de un sujeto usando un algoritmo patentado que combina aceleración, flujo de calor y otros parámetros. Sin embargo, no está claro qué porcentaje de cada parámetro (> 20 parámetros totales de salida) contribuyen a la ecuación de predicción.

Intille et al. (12) han debatido recientemente la tendencia que hay que seguir para poder evolucionar en este sentido en los próximos 5 años:

- Dispositivos que sean capaces de registrar y almacenar en memoria interna el resumen por meses o datos en bruto (+60Hz, tres ejes) durante 1 semana o más en una sola carga. Los dispositivos tendrán aproximadamente el mismo tamaño o más pequeño que los dispositivos existentes.

- Los investigadores deberían tener la capacidad de cambiar el enfoque de sus medidas, llegando a proporcionar datos que sean comunes a partir de las señales del acelerómetro. Los esfuerzos para definir las normas para la validación cruzada de cada dispositivo pueden agilizar estos cambios.

- Los sensores deberán ser suficientemente pequeños y fáciles de portar de modo que los participantes puedan llevar más de un sensor en diferentes partes del cuerpo o bajo la ropa de manera cómoda.

- Los sistemas pueden mejorar la detección de la cantidad y tipo de actividad usando algoritmos estadísticos de reconocimiento de patrones que utilizan, no sólo las características de movimiento de los acelerómetros, sino también la información de otros tipos de sensores (por ejemplo, la ubicación).

A su vez, a más largo plazo, se podría llegar a conseguir:

- Desarrollar un programa que pueda estar asociado a los teléfonos móviles, por medio de “app store”, y así descargar los datos directamente.

- Emplear formas divertidas de enseñar a los participantes a utilizar y llevar los dispositivos mientras se realiza la recogida de datos.

- Detectar el nivel general de actividad física si se lleva en el bolsillo o en la cadera.

- Detectar los tipos específicos de actividad física como caminar, posturas e incluso actividades de resistencia si se utiliza con uno o más dispositivos inalámbricos adicionales que se comunican con el teléfono.

- Proporcionar a los participantes una retroalimentación audiovisual del sistema para saber si se está usando correctamente.

- Facilitar al participante un feedback con la información detectada de la actividad física con aplicaciones de vigilancia de la salud, gestión del tiempo o incluso juegos.

- Transmitir los datos sobre la actividad física a los investigadores diariamente.

- Crear a largo plazo, para los investigadores, mapas de actividad superpuestos segundo a segundo con el lugar donde se realiza la actividad.

- Ofrecer nuevas oportunidades para crear intervenciones que influyan en el momento de toma de decisiones con la medida, con un feedback inmediato.

Intille et al. (12) informan que algunos de los dispositivos que están en uso actualmente, podrán estar con un funcionamiento idéntico durante los próximos 10 años. Los componentes electrónicos internos, firmware y protocolos inalámbricos de chips serán propensos a cambiar a medida que las antiguas tecnologías se vayan suplantando por la mejora de los dispositivos o por el descenso del coste económico. Para maximizar el efecto de la investigación en la actividad física que se lleva a cabo hoy en día, los investigadores deben esperar y planificar un cambio mientras explotan plenamente el potencia de los nuevos dispositivos.

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CAPITULO DE LIBRO:

"Accelerometers: types and applications". En "Accelerometers: Principles, Structure and Appliacions"

Santos-Lozano A, Marín PJ, Garatachea N. Accelerometers: types and applications. En Accelerometers: Principles, Structure and appliacions. Editor Paulo Sérgio de Brito André. Editorial Nova. 2013. In press.

Chapter

ACCELEROMETERS: TYPES AND APPLICATIONS

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ABSTRACT

Accelerometer monitors have significant advantages when compared with other quantitative methods for measurement of energy expenditure. Accelerometers are currently used mainly in a research setting; however, with recent advances, incorporation into clinical and fitness practice is possible and increasing.

The main purpose of this chapter is to address the types of accelerometer-based assessments of physical activity and its applications in exercise science.

Different commercial models available in the market for research or professional purposes are analyzed. Special interest is also put on recently updated Actigraph technology (GT3X model). We report our novel results in relation to intra- and inter-instrument reliability of the ActiGraph GT3X accelerometer during both mechanical and biological conditions.

Methodological issues are addressed in regards to monitor placement, epoch duration, number of days worn, compliance to accelerometer protocols.

INTRODUCTION

Physical activity (PA), defined as any bodily movement produced by skeletal muscles that results in energy expenditure [1], has been identified as priority area in general health promotion as well as a specific objective for the nation's health (U.S. Department of Health

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and Human Services, 2000). In view of the prevalence, global reach, and health effect of physical inactivity, the issue should be appropriately described as pandemic, with far-reaching health, economic, environmental, and social consequences (Kohl et al., 2012).

As reported by Kohl et al. [2], theoretically, prioritisation for public health action is informed largely by three factors: the prevalence and trends of a health disorder; the magnitude of the risk associated with exposure to that disorder; and evidence for effective prevention and control. From this point of view, to get more insight into the interaction between daily PA and health, an objective and reliable methods for the assessment of PA in free-living subjects is required.

The method should be suitable to measure PA in large populations over relatively long and representative periods, and with minimal discomfort to the subjects. There is already a large number of techniques for the assessment of PA, which can be grouped into five general categories: behavioural observation, questionnaires (including diaries, recall questionnaires and interviews), physiological markers (like heart rate), calorimetry and motion sensors [3].

Although it appears clear that double labelled water and direct calorimetry are adequate criterion methods, the greatest obstacle to assessing free-living PA in humans has been the lack of a valid field method. The intercorrelation of various field methods may be of some value, but because there are errors in all methods it is impossible to determine the true validity of any one of them in doing so [4]. Table 1 shows the advantages and disadvantages of the five categorized techniques for the assessment of PA.

Table 1. Advantages and disadvantages of the techniques for the assessment of PA

Methods	**Advantages**	**Disadvantages**
Behavioural observation	Best recording of type of PA and interpretation of the activities Contextual information	Time consuming Limited in monitoring time Subjectivity of the observer
Questionnaires	Applicable in epidemiological studies Valid for gross classification of PA level	Limited validity No detailed information of PA
Physiological markers (heart rate)	Energy expenditure pattern is obtained	Only valid for a specific range of heart rate Some factors (hydration, temperature, emotion…) could limit the use
Calorimetry	Accurate and valid measurement of short term energy expenditure	Expensive Limited to laboratory setting until better portable devices
Motion sensors	Lightweight, portable Simple and inexpensive Non-reactive Free living conditions	Only number of steps Limited validity for energy expenditure estimation No information of specific activity

Motion sensors meet the criteria of being objective and suitable to measure PA in large populations over periods long enough to be representative of normal daily life and with minimal discomfort to the subjects. Motion sensors for the assessment of PA have evolved from mechanical devices like pedometers to electronic accelerometers. This chapter is focuses on the use of accelerometers in human population.

Accelerometers for the assessment of PA, are based on the measurement of body movement, that is, the dynamic component of PA. Accelerometers cannot be used to measure the static component in exercises, like weight lifting or carrying loads. However, in normal daily life, it is assumed that the effect of static exercise on the total amount of PA is negligible.

At 90´s, accelerometry was still considered to be in the developmental stage and in 1999 the meeting "Measurement of Physical Activity" was hosted in the Cooper Institute. Some conclusions and future recommendations about accelerometry were given to scientific community. Since then, the researchers have dedicated high efforts to respond the need for improvements in this field with technological developments and novel applications of existing and new technology. The published scientific literature provides a demonstration of the magnitude of this response.

In the last decade, accelerometers have gained acceptance as perhaps the most effective way to obtain objective information about PA levels in the population [5]. The most notable of this development has been the proliferation of monitor devices that provide an estimation of frequency, intensity and duration of PA performed by the subject who wore the monitor [6]. Due to these, we invite to the reader to a deeper understanding of these activity monitor through the currently technology (types and models), as well as the methodological issues.

ACCELEROMETERS: TYPES AND MODELS

Specific Accelerometers to Assess Physical Activity

Accelerometers are small, portable, lightweight and noninvasive device that measure body movement in terms of acceleration - change in the speed with respect to time - in one (uniaxial) or more planes (biaxial and triaxial accelerometers records motion in two and three planes respectively). Like acceleration is proportional to the external force involve, and directly reflective of energy expenditure, measuring physical activity using acceleration is preferred to using speed - change in position with respect to time-.

The measure of acceleration by the monitor device provides reliable information on mobility and objective measurement of physical activity like the frequency, intensity and duration of the movement. The most commonly used accelerometers use one or more piezo-electric sensors consisting of a piezo-electric element and a seismic mass, housed an enclosure [7] which measure acceleration due to movement. There are two main types: the cantilever bean and the integrated chip sensor.

- The cantilever bean technology is named for the beam that is attached to a support at one side that contains a piezoelectric element and a seismic mass (8, 9), which were typically installed manually by experienced technicians and calibrated during manufacturing process. The seismic mass causes the piezoelectric element crystal to experience deformation in the bending and record a voltage signal, proportional to the acceleration detected. The piezo-electric element is most sensitive in the bending direction (often referred as uniaxial), although deformations in other planes can result in accelerations signals too and for this reason some define like omnidirectional. The difference in sensitive in each direction is determined by the geometry, material property and the position of the seismic mass on the bean. However, the contributions from each plane in the output of these accelerometers, which combine signals from all directions (vertical to ground, horizontal and lateral), are not differentiable.

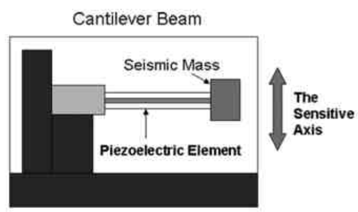

Figure 1. Cantilever bean sensor diagram

- The integrated chip sensor has a piezoelectric element and seismic mass that sits directly over a piezoelectric element and detect acceleration; the sensor is enclosed in a package that is directly attached in an electronic circuit board. The size of this integrated sensor is smaller than cantilever bean technology, so different sensors can be packaged into a signal sensor enclosure using precision machine assembly to measure movements in several planes. The newer devices use integrated chip sensors because this technology showed enhances in durability and repeatability of the monitors compared to the previously cantilever bean technology. Combined wit improved microprocessors, expanded onboard memory, extended battery life, and wireless communication (9). Moreover, these improvements have permitted physical activity measurement for longer periods and with higher time resolutions than before.

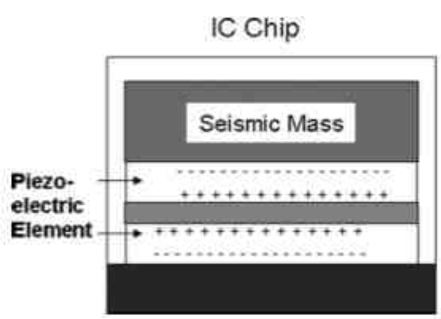

Figure 2. Integrated chip sensor diagram.

The accelerometer raw outputs in physical activity monitors are known as counts; however, it is often unclear what a count really means. For this reason, translating counts into a quantitative estimate of energy expenditure or the related categorical measure of time spent in light, moderate or vigorous intensity activity makes the data more useful for multiple applications [10]. Moreover, like the counts from the different monitors cannot be directly compared across monitors because of differences in how the raw data is collected, processed, filtered and scaled [7] present the results in metabolics units or physical activity level could be easier to make comparisons across studies [11]. So using specifically cut-point threshold or algorithms to convert the counts in physical activity level or energy expenditure must be applied.

Several monitors are available to measure physical activity and the most part of they record step numbers too. The selection of the monitor device depends on the study aims, the target population, the activity component of interest and the feasibility of the work (cost and logistics).

Below and in table 1.1 are presented a summary of the most used commercially available monitors device with its main features.

- The GT3X+ (figure 3) is the newest triaxial Actigraph accelerometer (Pensacola, FL, USA). Its weight is 19 g and its dimensions are 4.6cm x 3.3cm x 1.5 cm and has a rechargable Lithium Ion Polymer battery, that allow records about 30 days of raw data collected at a 30 Hertz. Moreover, it is water resistant and can withstand submersion at depths to 1 meter for up to 30 minutes. It uses a solid-state tri-axial accelerometer to collect motion data on three axes: vertical (Y), horizontal right-left (X) and horizontal front-back axis (Z). The Actigraph output also includes the VM. The ActiGraph GT3X+ records time varying accelerations ranging in magnitude from +/- 6 g's. The accelerometer output is sampled by a twelve-bit Analog to Digital Convertor according to end user settings, which can range from 30 Hz to 100 Hz. This raw acceleration is then stored in non-volatile flash memory (256MB). The GT3X+ also contains an Ambient Light Sensor, photodiode based light sensor with a range of 350 to 800 nm (600 nm peak), providing valuable information about the subject's environment. The GT3X+ communicates via high speed USB 2.0 connection, capable of downloading a single device.

Figure 3. GT3X+ Actigraph accelerometer.

- The Actigraph GT3X (figure 4) monitor device (Actigraph, Pensacola, FL, USA) is lightweight (27 g), compact (3.8 x 3.7 x 1.8 cm) and has a rechargeable Lithium Polymer Battery (12). It must be worn at the waist using a belt clip or elastic belt. It uses a solid-state tri-axial accelerometer to collect motion data on three axes: vertical (Y), horizontal right-left (X) and horizontal front-back axis (Z). The Actigraph output also includes the VM. The GT3X measures and records time-varying accelerations ranging in magnitude from ~0.05 to 2.5 Gs (13). The accelerometer output is digitized by a twelve-bit Analog to Digital Convertor (ADC) at a rate of 30 Hz (12). Once digitized, the signal passes through a digital filter that band-limits the accelerometer to the frequency range of 0.25 to 2.5 Hz (12). Each sample is summed over an 'epoch' and the output of the Actigraph is given in `counts´. The counts obtained in a given time period are linearly related to the intensity of the subject's physical activity during this period.

Figure 4. GT3X Actigraph accelerometer.

- The GT1M (figure 5) (Pensacola, Fla.; mass, 27 g; width, 38 mm; height, 37 mm; thickness, 18 mm) is one of the most used accelerometers in research, however today is not available in the market. It uses a uniaxial accelerometer to sense vertical accelerations, which range between 0.05 and 2.0g however in its final version (V3) it is possible obtain counts from two axes. The accelerometer signal is digitized by an analogue to digital converter, at a rate of 30 Hz. The accelerations are summed for a specified time period (i.e., epoch), and reported in the form of an activity count. The GT1M has 1 mega- byte of non-volatile flash memory, which supports 364 days of activity count data, or 182 days of activity count plus step count data if a 1 min epoch period is used. The GT1M utilizes a single-cell prismatic lithium ion rechargeable battery (3.7 V). The unit can be recharged in several hours by plugging it into a USB port on a computer, via a standard 2.0 interface cable or a 7-terminal charging hub, which is plugged into an electrical outlet. The life of the rechargeable battery is approximately 14 days.

Figure 5. GT1M Actigraph accelerometer.

- The Actitrainer (figure 6) is 8.6cm x 3.3cm x 1.5cm and its triaxial accelerometer is a solid state accelerometer. The measures and records time-varying accelerations ranging in magnitude from +/- 3 Gs, allowing a sample rate of 30 Hz. Moreover, the monitor has a Organic LED (OLED) display which allows the user to monitor certain activity parameters and device battery voltage in real-time. The ActiTrainer has 4MB of non-volatile memory, and its rechargeable battery is capable of providing power for 7 days with the display enabled or 10 days with it disabled. The unit can be recharged in several hours by plugging it into a USB port on a computer, via a standard 2.0 interface cable. The ActiTrainer's photodiode based light sensor objectively measures and records ambient light levels. With a measurement range of 350 nm to 800 nm (600 nm peak), a high sensitivity, and a linear response, the ActiTrainer's light sensor provides valuable information about the subject's environment.

Figure 6. ActiTrainer accelerometer.

- The Actical (figure 7) is 37 x 29 x 9 mm, weight 17 g and is water resistant. The Actical accelerometer has an omnidirectional sensor; it is worm on the hip, so the monitor is most sensitive to vertical accelerations. The sensor functions via a cantilevered rectangular piezoelectric bimorph plate and seismic mass, and it is capable of detecting movements in the 0.5- to 3-Hz range. Voltage generated by the sensor is amplified and filtered via analog circuitry. The amplified and filtered voltage is passed into an analog to digital converter, and the process is repeated 32 times per second (32 Hz). The resulting 1-s value is divided by four, and then added to an accumulated activity value for the epoch.

Figure 7. Actical accelerometer.

- The BioTrainer Pro (IM Systems, Baltimore, MD) (figure 8) contains one accelerometer that is positioned at an angle of 45º, which measures acceleration in both the vertical and the horizontal plane. Data is digitally sampled at a rate of 30 Hz, accumulated in 15 s, 30 s, 1 min, 2 min, or 5 min epochs and saved as either absolute "g" units or converted to calories burned. A large LCD readout provides for immediate visual feedback or the display can be disabled.

Figure 8. Biotrainer Pro.

- Research Tri-axial accelerometer (RT3) (figure 9). This accelerometer (Stayhealthy Inc., Monrovia, CA) is a three- dimensional accelerometer. The Triaxial Research Tracker is built using the original TriTrac-R3D technology. It is small (68 x 48 x 18 mm), light- weight (62.5 g), and can store data for up 21 days. It uses piezoelectric accelerometers that measures motion in three orthogonal dimensions and provides triaxial vector data in activity units.

Figure 9. RT3 accelerometer.

- The Kenz Lifecorder EX (Suzuken, Co. Ltd., Nagoya, Japan; weight, 60 g; width, 72.5 mm; height, 41.5 mm; thickness, 27.5 mm) (figure 10) utilizes a ceramic piezoelectric uniaxial accelerometer sensor that samples vertical accelerations at a rate of 32 samples second–1 (range, 0.06–1.94g). The accelerometer signal proceeds through an analogue bandpass filter, and is then digitized. The Kenz Lifecorder EX is powered by a standard no rechargeable lithium battery (CR2032). The data can be viewed on an external dis- play or can be downloaded to a computer with a USB cable. The KL has a memory capacity of 200 days.

Figure 10. Kenz Lifecorder EX.

- The Actiheart (CamNtech, Cambridge, UK) (figure 11) is worn on the chest. It consists of two electrodes connected by a short lead which simply clip onto two standard ECG pads. The Actiheart measures and records time-varying accelerations ranging in magnitude from ~ -2.5 to 2.5 Gs, with a resolution of 8 Bit (0.2m.sec-2 or 0.02g) and a frequency range of 1Hz to 7Hz, allow a sampling rate of 32 Hz. It contains a battery (21 day maximun battery life) which is recharged via a purpose built USB interface, which allows data transfer to the PC for setting up the Actiheart and analysing the data using custom software. The raw data is held in a database and can be edited with full traceability and can also be exported for manipulation.

Figure 11. Actiheart 4.

- The ActivPALTM (figure 12) is a relatively new accelerometer device, used to measure free-living activity and sedentary behaviour. The ActivPALTM is a 53 x 35 x 7 mm, single-unit, light weight (15 g) and developed by PAL Technologies (Glasgow, Scotland). The ActivPALTM need to be worn on the thigh using a layer hydrogel. It contains a piezoresistive accelerometer (uniaxial) and can determine different postures based on the inclination of the thigh. This device classifies an individual activity into three different categories (sitting, standing, and stepping). The life of the rechargeable battery is approximately 8 days.

Figure 12. ActivPal accelerometer.

- Intelligent Device for Energy Expenditure and Activity (IDEEA) (figure 13) is a monitor that analyses body motion, measure PA, monitor behaviour patterns, and estimate energy expenditure in a free-living situation on 24-hr basis. Five sets of sensors being able to measure angles of body segments and movement (acceleration) in 2 orthogonal directions. The monitor requires a one standard size AA alkaline battery, normally lasts 60 hours. The size of the monitor is 7 x 5.4 x 1.7 cm and weight 59 gram (including battery). Each sensor is 18 x 15 x 3 mm size and 2 gram of weight.

Figure 13. Intelligent Device for Energy Expenditure and Activity (IDEEA).

- The SenseWear Armband (figure 14) is a monitor used to measure steps per day, total daily energy expenditure and PA energy expenditure. The monitor recorded the acceleration of movement, as well as, body temperature and heart rate. This monitor calculates wear time itsellf.

Figure 14. SenseWear Armband.

Actigraph: Accuracy and Intermonitor Variability

A mechanical device is commonly used to assess inter-monitor variability because provides a standardized amount of acceleration [14]. Recently our research group assessed the intra- and inter-instrument reliability of the GT3X accelerometer using a vibration plate on each orthogonal axis (Y, X and Z axes) and at five frequencies of motion (1.1, 2.1, 3.1, 4.1 and 10.2 Hz) [15].

Table 2. Sumary of monitor device and its characteristics

Monitor	Distribuitor web site	Sensor	Raw data outcomes	Minimum Epoch Lengh/ Output Data aggregation	Batery life (days)
GT3X+	www.theactigraph.com	Triaxial accelerometer	Activity counts Steps	Raw data	30
GT3X	www.theactigraph.com	Triaxial accelerometer	Activity counts Steps	1 s or raw data	20
GT1M	www.theactigraph.com	Triaxial accelerometer	Activity counts Steps	1 $s \cdot epoch^{-1}$	20
Actitrainer	www.theactigraph.com	Triaxial accelerometer	Activity counts Steps HR	1 $s \cdot epoch^{-1}$ 15 $s \cdot epoch^{-1}$ with HR	14
Actical	www.actical.respironics.com	Omnidirectional accelerometer	Activity counts Steps	15 $s \cdot epoch^{-1}$	180
Biotrainer Pro	www.imsystems.net	Biaxial accelerometer	Activity counts Estimated Energy Expenditure	Variable (15 s to 1 min)	180
RT3	www.stayhealthy.com	Triaxial accelerometer	Activity counts Steps	1 $s \cdot epoch^{-1}$	60
Kenz Lifecorder EX	www.new-liestyles.com	Single-axis accelerometer	Activity counts Frequency counts	4 s·day	150
Actiheart	www.camntech.com	Omnidirectional accelerometer	Activity counts HR	15 $s \cdot epoch^{-1}$	21

Table 2. Continued

SenseWear	sensewear.bodymedia.com	Uniaxial accelerometer	Steps Heart Rate Energy Expenditure Acceleration Sleep duration Lying down time		
IDEAA	www.minisun.com	Five biaxial sensor	Daily activities Energy Expenditure Physical activity pattern Hear Rate	1 s·epoch	
ActivPal™	www.paltechnologies.com	Single-axis accelerometer	Time sitting, lying, walking and quite standing.	15 s·epoch^{-1}	8

Adapted of Welk et al. [11].

Ten GT3X monitor device were placed on the vibration table secure and firmly avoiding unwanted movements or accelerometer misalignment. The vibration table was driven by a trifasic motor (JL 712-2 type). As the vibration would only occur along the Y axis (Figure 15A) each frequency was repeat once an axis (Figure 15B and 15C). Vibration of the table commenced at a frequency of 1.1 Hz and thereafter increased to 2.1, 3.1, 4.1 and 10.2 Hz respectively. Each frequency was maintained for 7 min. Amplitude was identical in the five testing conditions (0.040 m).

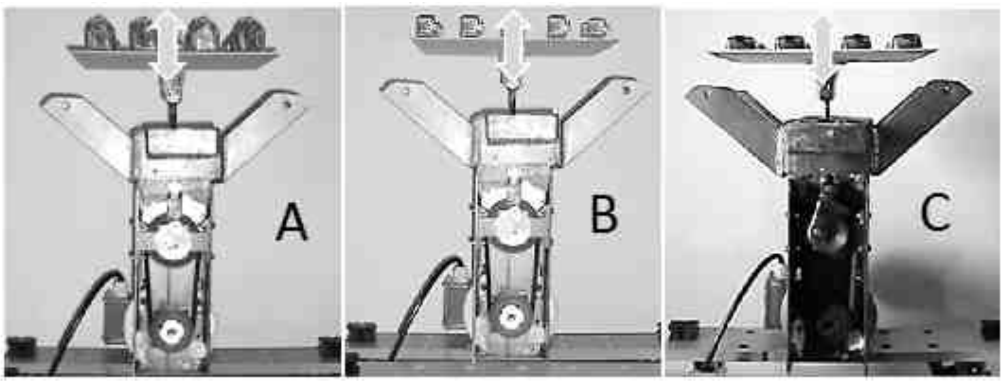

Figure 15. Vibration setup along the Y (A), X (B) and Z (C) axis. The arrow indicates the direction of movement of the vibration table [14].

These five frequencies of motion were selected to provide a variety of physiologically relevant accelerometer counts (from light to vigorous) within the limitations of the vibration table [16]. Moreover the result of higher frequencies out of the range of human motion are relevant to assessed the technical variability of the monitor [17].

After the analysis we found overall high intra-and inter-instrument reliability (table 3 and 4), for the frequencies between 2.1 and 4.1 Hz. In general, our data results support the use of the GT3X accelerometer as a reliable tool to estimate free-living physical activities in human studies, at least within those frequencies that are common to most types of daily activities.

Table 3. Intra-instrument coefficient of variation for the mean activity counts recorded at each axis and frequency

Frequency (Hz)	Axis Y (%)	X (%)	Z (%)
1.1	18.5% (0.0-105.0)	0.4% (0.0-4.0)	11.5% (0.0-54.0)
2.1	1.3% (0.5-2.1)	1.7% (0.6-3.7)	2.5% (0.6-4.9)
3.1	0.8% (0.5-1.5)	0.4% (0.6-4.9)	0.6% (0.3-1.2)
4.1	1.3% (0.6-2.3)	0.8% (0.2-2.6)	1.1% (0.4-2.2)
10.2	27.3% (8.6-52.9)	22.5% (2.61-48.3)	8.6% (5.1-19.5)

Data are shown as mean and range (min-max).

Table 4. Inter-instrument coefficient of variation for the mean activity counts recorded at each axis and frequency

	Axis		
Frequency (Hz)	**Y (%)**	**X (%)**	**Z (%)**
1.1	201.8%	287.0%	149.4%
2.1	3.1%	9.9%	9.2%
3.1	2.2%	1.2%	1.5%
4.1	3.7%	7.6%	6.8%
10.2	67.3%	99.5%	52.6%
Overall mean	55.6%	81.0%	43.9%

Next to the GT3X technical variability work, we also evaluated the intermonitor reliability over a range of real physical activities (18): rest, walking (4 and 6 km·h-1), running (8 and 10 km·h-1) and repeated sit-to-stand (40 times·min-1).

High Intra-class correlation coefficients (ICC) values were found in all axes (table 5). With regards to each axis: (i) Y-axis, ICC values ranged from 0.925 to 0.998; (ii) X-axis, ICC ranged from 0.933 to 0.998; (iii) Z-axis, high ICC values were also found (range: 0.985-0.997); and (iv) VM, the values of ICC ranged from 0.946 to 0.998.

Table 5. Intra-class correlation coefficients (ICC) by axis and activities

	Monitor placement	**Sit-Stands**	**4 km·h^{-1}**	**6 km·h^{-1}**	**8 km·h^{-1}**	**10 km·h^{-1}**
Y	Right	0.993	0.995	0.998	0.997	0.997
	Left	0.996	0.950	0.996	0.991	0.925
X	Right	0.976	0.991	0.989	0.978	0.933
	Left	0.984	0.998	0.994	0.994	0.947
Z	Right	0.996	0.994	0.994	0.997	0.996
	Left	0.992	0.996	0.995	0.994	0.985
VM	Right	0.991	0.987	0.997	0.993	0.983
	Left	0.984	0.984	0.998	0.982	0.946

$P < 0.01$ for all ICC values.

Abbreviation: VM, vector magnitude.

Intermonitor coefficients of variation (CV inter) values are shown in table 6. The CV inter for rest was omitted to the analysis due to the very low mean score. With regards to each axis: (i) Y-axis, CV inter values ranged from 20.4 to 1.4%, with the lowest CV inter value corresponding to running at 8 km·h-1; (ii) X-axis, CV values were very high among conditions (range: 45.3-9.1%); (iii) Z-axis, for sit-stand condition CV values were the highest; and (iv) VM, all the CV values were ≤14.9% except for right monitor placement in sit-stands (23.0%). Similar to Y-axis, the lowest CV inter values in VM corresponded to 8 km·h-1.

Table 6. Inter-monitor coefficients of variation (CV, in %) by axis and activities

	Monitor placement	Sit-Stands	4 km·h^{-1}	6 km·h^{-1}	8 km·h^{-1}	10 km·h^{-1}
Y	Right	20.4	12.7	12.3	1.6	3.4
	Left	12.3	14.5	4.5	1.4	2.1
X	Right	21.6	12.8	9.1	19.9	29.9
	Left	22.5	18.4	12.3	45.3	34.3
Z	Right	23.2	2.2	3.5	13.7	16.3
	Left	12.4	10.6	10.7	19.6	5.5
VM	Right	22.3	9.2	8.1	1.1	5.8
	Left	14.9	7.0	6.5	1.1	2.7

Abbreviation: VM, vector magnitude.

An overall good inter-instrument reliability of the GT3X accelerometer across all planes were found. Our result also suggest that the addition of the X and Z-axis does not provide further benefits to assess the movement in typical PA compared with 'classical' uni-axial (Y-axis) assessment of activity counts.

New Trends: Smartphones Accelerometers

Over the past decade, mobile phones have changed radically, from modest call devices to the sophisticated computers known as smartphones. Nowadays, these devices allow individual users to install specialized applications of their choosing. It is estimated that 500 million people globally, out of a total of 1.4 billion smartphone consumers, will be using health-related smartphone applications by 2015 [19].

Activities such as sitting, standing, walking, and running can be recognized from mobile phone accelerations. Recently, Carlson et al., concluded that in both men and women, smartphone derived activity counts strongly correlate with treadmill gait speed over a wide range of subject ages and weights [20]. Outside the fitness centre, the smartphone accelerations and/or global positioning system (GPS) technology is being used to quantify physical activity (see Figure X).

Figure 16. RunKeeper application for IOS system.

On the other hand, according to Lee RY et al., 2011 the fall detection using a mobile phone is a feasible and highly attractive technology for older adults, especially those living alone (21). It may be best achieved with an accelerometer attached to the waist, which transmits signals wirelessly to a phone. Alternatively, there is an application (GymSkill) for Android system that utilizes the embedded sensing capabilities of a smartphone placed on the balance board (accelerometer and gyroscope) to record the exercises. The quality of recorded data is automatically evaluated, i.e.; the skill of the subject is assessed. The system provides basic situated (visual and auditive) feedback during physical exercise and, moreover, performs retrospective automatic assessments of the quality of the performed exercises. It provides a global numerical judgment of physical exercises in the form of an aggregated skill metric, which is the basis for competitive evaluations of physical exercises. It is, thus, ideal for tracking individual progress over the course of a long-term training program (22) (See figure 17).

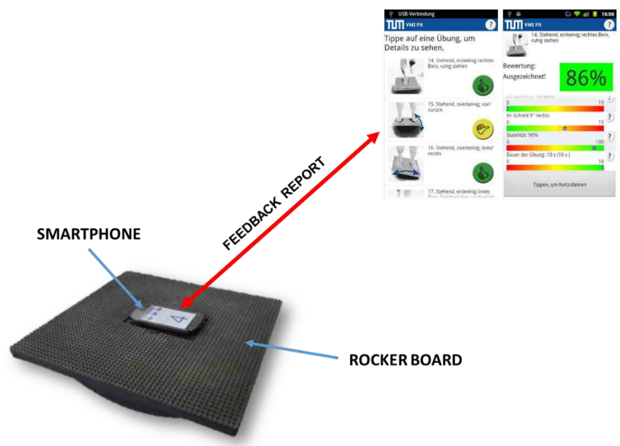

Figure 17. GymSkill application for Android system.

METHODOLOGICAL ISSUES

There are some methodological issues that could affect the accelerometer output, such as: monitor settings, number of days worn, the monitor placement and the compliance of the protocol for the research and user.

Settings

The most part of monitor models available for research have in common the need of a pc monitor interface to initiate and setup each single unit. Each accelerometer model have its own software to initialize the monitor, defined initializer like the process of preparing a PA monitor to collect data.

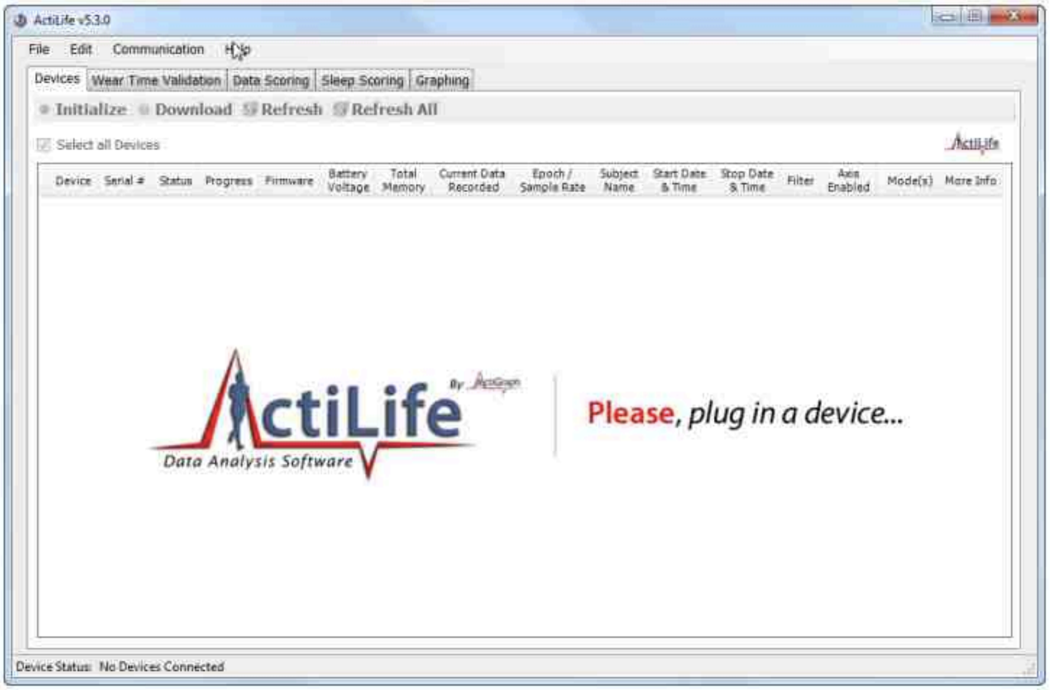

Figure 18. Screenshot of the Actigraph software "Actilife 5.3.0" extracted of the Actilife manual [12].

Band Pass Filter

The selection of an appropriate frequency response range for a bandwidth filter could be significant. The general frequency in normal nonimpact PA of the center of mass in human is below to 8 Hz and the upper limit could be nearby as 25 Hz in specific movements of the arms [23].

The sampled data is filtered using a band pass filter by the sensor output. The band pass filtering lets pass frequency between a preset low and high frequency, which increases the linearity of the output with the true signal. Moreover, this band pass filter decreases the influence of artifacts or electric/electrical noise.

The existing monitors use band pass filter ranged between 0.25 to 7 Hz, and some monitor offer the possibility to choose the value of the filter. So this filter would discriminate noise that are not physiological and not including in the output signal.

Epoch

Epoch duration can affect the interpretation of data. An epoch is a user-define time interval over which the activity monitor information is summarized [24]. This choice is intimately related to PA outcome variables. Choosing a short epoch offers higher resolution of bout duration, and is important if the PA is accumulated in several short events.

The traditional epoch in adults has been 60 s and the most published calibration studies have used this time epoch to establish relationships between activity counts and energy expenditure. However, in children the use of shorter epoch improve the accuracy of the results (<5 s-epoch) because they development shorts bouts of activity. The currently accelerometer technology and the higher levels of storage memory in the newest accelerometers over the first generations provide the possibility of storage the data in RAW data, that guarantees retain much information and exits the option to select the epoch after the register. However, if the monitor selected does not provide this option or is impossible for methodological question (as smaller epoch the total battery life and memory capacity is reduced) the best choose is select the shortest epoch possible to recollect the maximal information about the original biosignal and before could be reintegrated in higher epoch if it is needed.

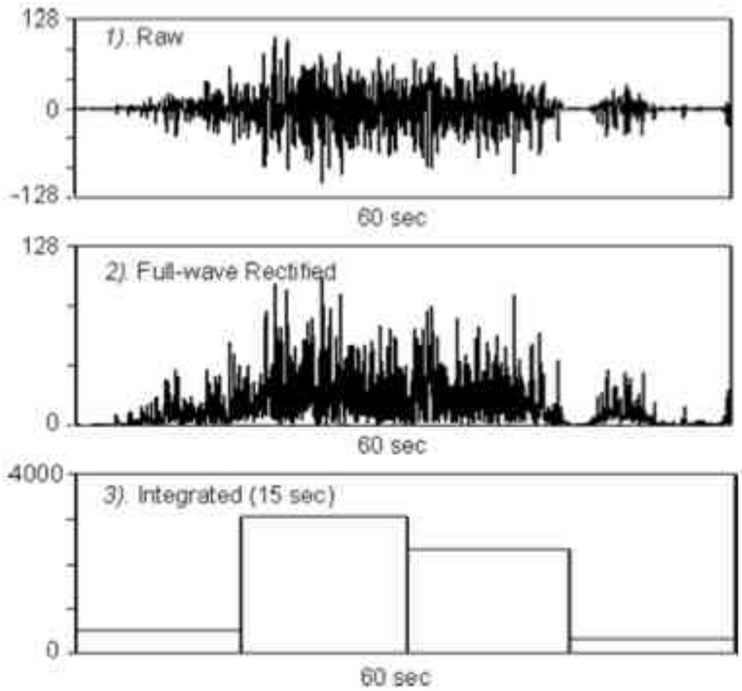

Figure 19. Analytical processing of acceleration data from RAW to 15 second-epoch (Adapted from Chen et al. 2005) [7].

Recording Start

The monitor should be programmed to start the recording the first day in which is worn by the participant, about midnight. Also, should be set to record for the maximum days possible for the monitor, in order to minimize faults.

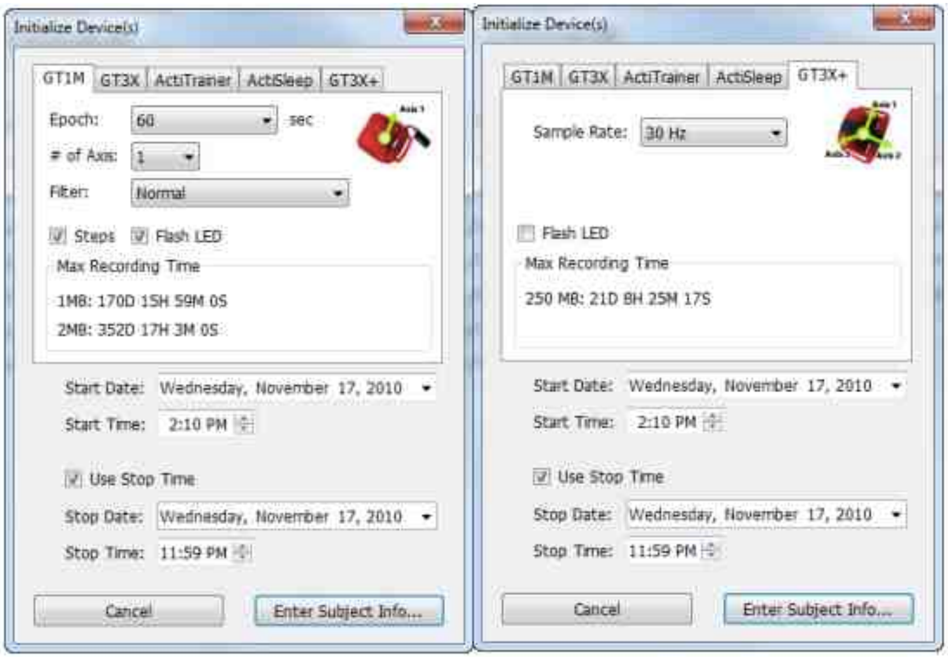

Figure 20. Screenshot of the initialize device interface in the Actigraph software “Actilife 5.3.0” extracted of the Actilife manual [12].

Number of Days Worn

Determining the correct monitoring period depends in part on the study design and objectives, and the cost of using monitors during several days. The proposed to choose the correct numbers of days is to quantify the variability in repeated measures of the behavior. To determine the number of days, most studies have employed variance partitioning techniques to estimate and calculate the correlation coefficient for a single day of monitoring as well as the Spearman-Brown prophecy formula obtained different results in young (children and adolescents) and adults, 4-9 days and 3-5 days respectively [25].

Normally, in PA monitor studies researches have chosen record 7 days because theoretically provide an enough number of days to register the variation and the routine of PA, and long-term studies measuring patterns of behavior need more days. Currently, studies checking the validation of several monitors used 4 days, two weekdays and two weekend days, to record the information.

However, not only the days wearing the monitor could affect to the output data, the hours per day monitoring have influence in the final record too. Typically, researches have used 24 hours per day or only the waking time as the sampling time to study. In fact, the decision depend the aim of the study and the target study population. In the last years agreement about the time per day that accelerometer must record has appeared around 10 hours per day [26].

In conclusion the number of monitoring days depend on the population target, the budget of the project, the research question of study among others. The researches have the final decision, but 3-5 days in adults (two weekend days) and 7 days for children and for adolescents during 10 hours per day look like a reasonable choose in PA monitor studies.

Monitor Placement

Monitors can be placed in several positions on the body, however the manufacturer recommends specific place to wear the accelerometer in function of the monitor characteristics. Ankle, wrist, back, waist or hip are the most typically placement used.

Ideally, the accelerometer should be attached as close as possible to body´s center of mass [27]. In spite of the monitor placement is an important methodological issue because the accelerometer output is dependent on the positioning on the body (the frequency and amplitude depend on the segment where the sensor is attached) and its orientation, researchers have not focus their studies in this consideration. To date, a small number of studies have specifically the objective to check the monitor placement notwithstanding its important.

The trunk localization, like hip or lower back, has become as the preferred position for the monitor placement and studies comparing different placement options indicate that accelerometers are best placed on the hip or the lower back [25]. Also, the most part of accelerometers are development to be place on this localization, could be place on the right or left side of the hip because there are not a criterion to choose the placement. While authors (28) did not report significant differences due to monitor placement others have also shown significant differences between right and left hip placement [18, 19, 30]. Thus, it is important to recommend that accelerometers be constantly worn in the same side in order to obtain reliable results, both across different individuals and within the same individuals across different days of monitoring. Like the most part of the people is right handed, the right hip could be the optimal to place the monitor [27].

Nowadays it is showed accelerometers places on the hip are not enough accurate measuring sedentary behaviors and PA at lowest intensities. For this, manufactures have started to develop new accelerometers to wear in other place to record these activities, such as the ActivPalTM. This new accelerometer is designed to place on the tight with a sticker, and using an inclinometer provides the time walking, standing and sitting.

Compliance to an Accelerometer Protocol

As important as the validity, calibration and the precision of an accelerometer is compliance with the monitoring protocol in any study using accelerometers to quantity PA behavior. It is a critical factor and no experimental studies investigating the efficacy of different strategies to promote compliance have been conducted yet. The goal of the strategies is that the individual wear the accelerometer the most part of the time defined. The best of the strategies may be the protocol education of the individual, explaining why, how and when must wear the monitor. However, the researchers may help to remember to the participants to wear the accelerometer [25].

To improve the compliance, the researchers could ask to participants complete a diary register noting the time in which is worn and removed, what activities was done wearing the monitor and what activities was done without the monitor, as well as any problem during the register time. Moreover, the diary is a great tool to clean, reduced the data and check the sensitive of the monitor differing among activities. In a similar way, participants could be ask to complete a simple log register the time in the morning in which the monitor is on and the time in which the monitor is off.

Make reminder calls, provide a tips or lists of frequently asked questions about the protocol, the goal study, how attach the monitor or another important information can to the participants to understand and promote compliance.

Also, display written material, like flyers, magnets or stickers, on visible place to prompt and remember the participants wearing the accelerometer is a good technique.

Figure 21. Example of flyer.

Another way to promote the compliance is to show an example of an output to participants to demonstrate that is possible know when they are not wearing the accelerometer. The goal is not intimidate participants, is use this technique inside the education process and improve the accountability.

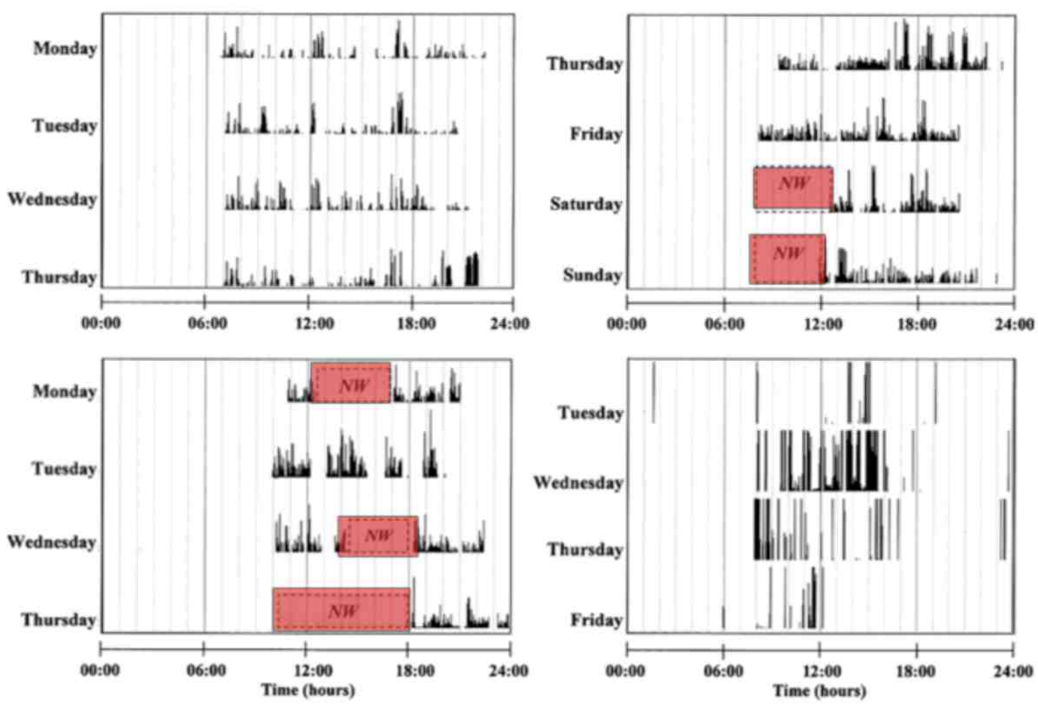

Figure 22. Time wearing the accelerometer and time no wearing the accelerometer. Adapted of Heil et al. [24].

Provide incentives contingent on compliance, such as gift certificate, extra credits, and coupons or, even, money based on the number of completed monitoring days help to wear the accelerometer the most part of the time.

Next table 7 show compliance strategies:

Table 7. Compliance strategies

Proposed strategies to promote compliance with activity monitoring
– Ask to complete an activity monitoring log. – Display written material/flyers on visible places to prompt wearing the accelerometer. – Make reminder calls. – Provide with tips or list of frequently asked questions on how to wear accelerometers correctly. – Show an example of an output to demonstrate that one can know when they are not wearing the accelerometer. – Provide rewards for compliance, such as gift certificate, extra credit, coupons, etc. – Inform on the study in advance to caregivers and educate them about wearing protocols.

Adapted from Garatachea et al., 2010 [8].

One weakness of accelerometers is that subjects may remove them periodically, more if the monitor is not waterproof, and this affect the total accumulated and average PA [26]. To solve this problem is needed to clean the data removing this time or do an established statistical procedure called imputation to reduce the biases caused by this lost time [31]. The imputation consists in inserting a constant value for this missing values (sleep time and time not wearing the monitor) reducing the problem and improving the PA estimated. However, this imputation not resolve the whole problem because the finally results tent to underestimate the true variance of the complete data set, so a multiple imputation is need avoids the problem.

Choosing an Accelerometer

Although many questions on how best to use accelerometers to measure PA remain unanswered, a considerable amount is known about monitor selection, quality, and dependability [27]. The decision to purchase a particular make and model of accelerometer is influenced by a multitude of factors. In general, no one monitor is superior to another, and selection depends primarily upon the research interest. However, for most researchers, the relative validity and interinstrument reliability of a given accelerometry product is of primary importance. According to Trost et al. [25], evidence indicates that some accelerometers may perform better than others under certain conditions, but the reported differences are not consistent or sufficiently compelling to single out one brand or type of accelerometer as being superior to the others.

Issues of affordability should be considered, because in a study of Conn and coworkers [32], participants wore the TriTrac units 78% of the requested days and under-reported time not wearing the TriTrac. In this case, authors concluded that researchers should provide for the possibility of damaged TriTrac devices. Therefore, when it comes to selecting an accelerometer, issues of affordability, product reliability, monitor size, technical support, and comparability with other studies may be equally as important as the relative validity and reliability of an instrument.

CONCLUSION

The tri-axial accelerometer is an objective method that can be used to distinguish differences in activity levels between individuals and to assess the effect of interventions on PA within individuals.

Several research labs and companies have set out to develop the next generation of monitors, which have implemented two separate strategies: a) they use multisensory arrays applied at different body segments (ankle, waist…) and b) they combine accelerometry with physiological sensor(s) (i.e. heart rate, temperature…) in a single site device.

Chen and Basset [7] in an interesting review concluded that future accelerometry monitors must be designed to significantly improve their ability to predict energy expenditure. Moreover, in order to be portable and rugged enough for free-living applications, several crucial criteria should be followed:

1) they should be compact and contain no or a minimum amount of wires, and
2) they must have sufficient data processing and storage capabilities to record continuous data for an extensive period.

However, before all these criteria are realized in an ideal PA monitor design, careful studies must elucidate the components of raw accelerations that significantly contribute to the accurate predictions of energy expenditure. Crucial advancements in this process could lead to major improvements in determining not only the optimum data-processing algorithms, but also optimum sensor placement.

Intelle and colleges [33] recently discussed several trends in sensor development that could evolve during the next 5 years. These trends are:

- More devices that take advantage of motion measurement in three dimensions may emerge, reducing device sensitivity to body orientation and/or allowing an estimate of work done by particular parts of the body (e.g., arms vs legs).
- Devices that log data using onboard memory will be capable of storing summary data for months or raw accelerometer data (60+ Hz, three axes) for 1 week or more on a single charge. These devices will be about the same size as or smaller than existing devices.
- Researchers will have the ability to change the focus of their measures from proprietary counts to summary data computed from raw accelerometer signals, where the summary feature computations are fully and openly described. This should facilitate comparison across different devices. Efforts to define standards for cross device validation and openness, such as in this supplement, can accelerate these changes.

- Sensors will be sufficiently small and convenient so that it will be possible to have participants comfortably wear more than one sensor at different body locations under clothing. Devices that integrate information from more than one body location may dramatically improve the fidelity of PA data that can be collected from participants.
- Systems may improve activity type and amount detection performance using statistical pattern recognition algorithms that use not only motion features from accelerometers but also information from other types of sensors (e.g., location).

In the longer term, the following could be possible for a system:

- Be downloaded from an ‘‘app store’’ directly into a standard mobile phone;
- Use entertaining ways to teach participants to use and wear it, while collecting training data;
- Detect overall PA level if carried in the pocket or on the hip;
- Detect specific types of PA such as postures, ambulation, and even resistance activities if used with one or more additional wireless devices that communicate with the phone;
- Provide entertaining audiovisual feedback to prompt participants when it is not working or being worn properly;
- Provide engaging feedback to the participant using the detected PA information, such as applications for health monitoring, time management, or even games;
- Transmit data about PA and compliance to researchers daily;
- Create long-term, second-by-second activity maps for researchers, overlaid on the location where the activity took place; and
- Provide new opportunities to create interventions that influence in-the-moment decision making with tailored, just-in-time feedback.

Intelle et al. [33] inform that few measurement devices in use today will be on the market 10 yr from now in an identical form. Internal electronic components, firmware, wireless chip protocols, and housings are all likely to change as old technologies are supplanted by improved or lower cost options. To maximize the effect of PA measurement research being conducted today, investigators must expect and plan for change so as to fully exploit the potential of the new devices on the horizon.

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