The ActiGraph counts processing and the assessment of vigorous activity

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Summary

The purpose of this study was to investigate the effect of the band-pass filter on the measurement bias with ActiGraph counts during high speed running and for estimating free-living vigorous physical activity (VPA). Two alternative band-pass filters were designed, extending the original frequency range from 0.29-1.66 (AG) to 0.29-4Hz (AC4) and 0.29-10Hz (AC10). Sixty-two subjects in three age groups participated in a locomotion protocol consisting of multiple walking and running speeds. The time spent in free-living VPA using counts generated with the different band-pass filters were evaluated in 1121 children. Band-pass filter specific intensity cut-points from both linear regression and ROC analysis was identified from a calibration experiment using indirect calorimetry. The ActiGraph GT3X+ device recording raw acceleration at 30Hz was used in all experiments. The linear association between counts and running speed was negative for AG but positive for AC4 and AC10 across all age groups. The time spent in free-living VPA was similar for all band-pass filters. Considering higher frequency information in the generation of ActiGraph counts with a hip/waist worn device reduces the measurement bias with running above 10 $km \cdot h^{-1}$. However, additional developments are required to accurately capture all VPA, including intermittent activities.

Keywords: ActiGraph, physical activity, filtering, algorithm

Introduction

The accelerometer devices manufactured by ActiGraph Inc. are widely used for the objective assessment of physical activity (PA) in epidemiological research (Migueles*, et al.* 2017). The output commonly used is named "counts" and is the result of several consecutive processing steps of acceleration (Tryon & Williams 1996). Counts is linear associated with energy expenditure (EE) for locomotion activities (Freedson*, et al.* 1998) although studies have identified a plateau effect or even an inverted-U phenomenon at speeds above 10 $km \cdot h^{-1}$ (Brage*, et al.* 2003). The measurement bias is proposed to originate from intrinsic properties of movement, placement of the activity monitor but also the narrow frequency band-pass filter included in the counts processing method (John*, et al.* 2012). A measurement bias with running above 10 $km \cdot h^{-1}$ has important implications for the assessment of vigorous physical activity (VPA) and consequently what intensities researchers recommend important for healthy behavior.

The band-pass filter implemented in the AG counts processing method allows acceleration in a frequency range of 0.29-1.66 Hz resulting in an amplitude attenuation of 50% at 0.25 and 2.5 Hz. The mean averaged deviation (MAD), Euclidian norm minus one (ENMO) and Activity Index (AI) have been proposed as alternative measures to counts not restricting the frequency range (Aittasalo*, et al.* 2015; Bai*, et al.* 2016; van Hees*, et al.* 2013). However, omitting noise reduction or error correction in the acceleration measurements seems to challenge the validity of measuring free-living PA in a noisy environment. Machine learning and multiple regression models have also been proposed to accommodate various measurement biases observed with the ActiGraph counts, although the plateau/inverted-U has not been specifically addressed (Crouter & Bassett 2008; Crouter*, et al.* 2006; Staudenmayer*, et al.* 2009).

The proprietary nature of the AG counts processing implementation does not allow researchers to directly consider alternative band-pass filters. However, this has been addressed in a recent study generating AG counts from raw acceleration measured with the Axivity AX3 (Brond*, et al.* 2017). The accuracy obtained clearly suggests a valid method for investigating the effect of using alternative band-pass filters with AG counts.

The purpose of this study was to investigate the generation of ActiGraph counts and the option to consider higher frequency information for reducing the measurement bias at running speeds above $10kmh^{-1}$ and the effect on estimating free-living VPA.

Methods

Study design and experiments

The objectives of this study were to design two alternative band-pass filters, extending the original frequency range of 0.29-1.66Hz (AG) to 0.29-4 Hz (AC4) and 0.29-10 Hz (AC10), and to evaluate the counts generated with a locomotion and population experiment. The locomotion experiment evaluates the AG, AC4 and AC10 counts during walking and running at different speeds and across three age groups. Whereas, the population experiment is used to evaluate free-living VPA using PA collected in a large population-study of children. A calibration experiment is used to establish band-pass filter specific cut-points for the classification of light, moderate and vigorous intensity domains identified by indirect calorimetry.

Instrumentation and counts processing

All participants in the three experiments were fitted with an ActiGraph GT3X+ activity monitor (ActiGraph LLC, Pensacola, FL) over the right hip at the level of the iliac crest using an elastic belt. All monitors were initialized using the ActiLife software (Version 6.11.7) to record raw acceleration data at 30 Hz sampling frequency. The raw acceleration data was loaded into Matlab (R2016 64bit) for processing into counts using the method described in (Brond, Andersen & Arvidsson 2017) and using the original band-pass filter (AG) in addition to the two alternative band-pass filters (AC4 and AC10). Only the vertical axis was considered in the analysis and an epoch length of 10 seconds was used. Before executing the locomotion and calibration protocol it was ensured that the devices position and orientation was similar for all subjects. The participants enrolled in the population study were asked to wear the ActiGraph GT3X+ for seven consecutive days during waken hours except during water activities (e.g. bathing, swimming, showering). An examiner supervised the participants face-to-face to attach the monitor over the right hip in an elastic belt around their waist.

Locomotion experiment

A convenient sample of 62 subjects divided into three age groups was invited to participate: 1) A children group with a mean (SD) age of 10.3 (0.3) included 22 participants (14 females) from the fourth grade of a local municipality school in Svendborg, Denmark, 2) an adolescent group aged 15.7 (0.3) had 20 participants (8 females) from the ninth grade of a municipality school in Malmö, Sweden, and 3) an adult group aged 24.7 (2.7) included 20 participants (5 females) from the institute of sports and biomechanics at the University of Southern Denmark, Denmark. An indoor 25 meters gym hall was used for children's group, an indoor 200 meters athletics track for the adolescent group and an outdoor 400 meters athletics track for the adults group. The adult group followed a protocol consisting of two walking speeds and one normal running and one fast running speed. The adolescents performed three walking speeds, one normal running and one fast running speed. The children protocol included three walking speeds, two running speeds and one fast running speed. Walking and running activities were initiated for all subjects in the group at the same time and continued for 120 seconds. The fast running was sustained for 30 seconds. All subjects were required to use the same group-pace during walking and normal running. For the final fast running speed, the pace was individually selected. All activities were separated by a 5-minute break. Activity start and end times together with distance were used to estimate the individual locomotion speed for all walking and running activities. The walking-running experiment did not require approval by an ethics committee. The participants received detailed information about the study protocol and verbally agreed to participate in the study.

Calibration experiment

Thirty-six children (third and fourth grade) were recruited from a local school in the Odense municipality. The children were recruited by email through the school office and word of mouth and informed consent was received from all participants and their parents. The children engaged in the experiment participated in a structured activity protocol consisting of three sedentary activities (sitting quietly, sitting playing IPad, standing playing IPad), two walking activities (preferred speed and brisk), a running activity (self selected running speed), an intermittent basketball activity, biking and a playground activity. The activity protocol was performed on and around the school area. Oxygen consumption was measured in the calibration experiment using the lightweight Metamax 3X (CORTEX Biophysik GmbH, Leipzig Germany) portable metabolic analyzer (Medbo*, et al.* 2002). The metabolic analyzer was worn on the back during execution of all activities. The measurements started after an adaption period of 10 minutes. The walking, brisk walking and running activities were performed consecutively in the order of intensity without breaks. A 2-5 minutes natural break were used between all other activities. The intensity of each activity was self-selected but subjects were also encouraged to adapt to an intensity they could complete the full duration of each activity. A log was used to record activity start times and to extract the individual activities from the raw data. The duration of each activity was 5 minutes and the first 60 seconds of data were excluded from the analysis. Total energy expenditure (TEE) was calculated as… Resting energy expenditure (REE) was estimated using the age and weight adjusted Schofield prediction equations and used to calculate the MET-value of each activity as the quotient TEE/REE (Herrmann*, et al.* 2017). The Ethics Committee of the Region of Southern Denmark approved the calibration study.

Cut-points

A total of six sets of cut-points were generated. Linear regression was used with four sets (REGI-IV) and receiver operating characteristics analysis was used with two sets (ROCI and ROCII). The REGI cut-points were determined by evaluating the linear association between counts (AG, AC4 and AC10) and EE (METs) using the data collected during standing, preferred walk, brisk walk and running. The REGII is similar to REGI although including the basketball activity. The REGIII is similar to REGI, although adding a squared term in the regression model to account for a potential curvilinear association. The REGIV cut-points were determined by evaluating the association between counts and METs during walking and running independently. This approach is inspired by the 2-regression model used by Crouter et al. (Crouter & Bassett 2008). The moderate and vigorous intensity thresholds were predicted using the 3 and 6 METs absolute intensities for all methods using regression (Garber*, et al.* 2011). The ROCI cut-points were determined as the optimal detection of the brisk walk activity with respect to preferred walk activity and vigorous intensity threshold as the optimal detection of the running activity with respect to the brisk walking activity (Jago*,* *et al.* 2007). The moderate cut-point threshold used with ROCII was determined by estimating the 95% upper confidence limit of the intensity generated during the walking at preferred speed activity whereas the 95% upper confidence limit of the intensity generated during brisk walking was used to define the vigorous intensity threshold cut-point. The same sedentary cut-point was used with all methods and determined as the maximum count value for the activities sitting, sitting playing tablet game and standing playing tablet games.

Population study

Evaluation of free-living PA was based on a large population sample of Norwegian fifth-grade children from the Active Smarter Kids (ASK)-study (Resaland*, et al.* 2015), conducted in Sogn og Fjordane county, Norway during 2014–2015. Sixty schools, encompassing 1202 children, fulfilled the inclusion criteria, and agreed to participate. This sample represented 86.2% of the population of 10-year-olds in the county, and 95.2% of those eligible for recruitment. Later, three schools encompassing a total of 27 children declined to participate. Thus, 1145 (97.4%) of 1175 available children from 57 schools agreed to participate in the study. Of these children, 1121 (97.7%) children provided at least one day of valid accelerometer data at baseline and were included in the study. The South-East Regional Committee for Medical Research Ethics in Norway approved the study protocol. We obtained written informed consent from each child's parents or legal guardian and from the responsible school authorities prior to all testing. The ASK-study is registered in Clinicaltrials.gov with identification number: NCT02132494. Data reduction, assessment of time spent at different intensity domains and statistical analysis was done in Matlab (R2016 64bit). A non-wear criterion of 60 minutes consecutive zeros not allowing for any sporadic activity was used (Aadland*, et al.* 2018), and daytime was restricted from 6AM to 11PM in addition to requiring 10-hour wear time to provide a valid measurement day. One-way ANOVA and

Tukey-Kramer multiple comparisons (Post-hoc analysis) were used to statistically test differences in time spent in the different intensity domains.

Results

Figure 1 presents the frequency response of the original ActiGraph filter (AG), and the AC4 and AC10 filters. The frequency response of AC4 and AC10 as compared to the AG clearly demonstrate that higher frequency components are considered. Below 0.75 Hz there is a minor difference in the attenuation as frequency decrease.

Figure 2 presents the counts generated with AG, AC4 and AC10 during walking and running at selected speeds and across the three age groups. The association between counts and locomotion speed below 10 $km \cdot h^{-1}$ seem linear with AG and for all age groups. The counts generated with both AC4 and AC10 during running as compared to walking is slightly elevated which seems to demonstrate a curvilinear association with locomotion speed below 10 $km \cdot h^{-1}$. In all age groups, there was a significant positive association between walking speed and counts for all three band-pass filters (all p-values<0.01). There was a significant negative association between running speed and AG counts in all age-groups (all p-values $<$ 0.01). In contrast, there was a significant positive association between running speed and counts for both the AC4 and AC10 in adults and adolescents (all p-values < 0.01), and a non-significant positive association for AC10 in children (p-value = 0.46). The association between running speed and AC4 counts in children was negative and borderline significant (p = 0.054).

The predicted REE of the children was 5.16 (SD: .57) $ml \cdot kg^{-1} \cdot min^{-1}$ and the measured intensity of the four activities preferred walk, brisk walk, basketball and running was 3.6 (0.44), 4.4 (0.5), 6.8 (0.96) and 7.3 (0.99) METs. The intensity range of all sedentary activities was 1.1-1.7 METs. The moderate and vigorous intensity cut-points estimated for each band-pass filter (AG, AC4, AC10) and with the six methods used (REGI, REGII, REGIII, REGIV, ROCI, ROCII) are presented in table 1. The sedentary cut-points for AG, AC4 and AC10 were 115, 576 and 768 counts per minute, respectively. Regression model performance and sensitivity and specificity of the ROC analysis are presented in the supplement 1.

Twenty-two subjects failed to provide at least one day with 10 hours of PA and were thus excluded from the analysis. The mean number of valid days for the 1121 subjects was 7 (SD: 1.5) and with a mean wear time of 13.1 (SD: 2.00) hours. The time spent sedentary, light, moderate and vigorously across the six analytical methods and aggregation methods (AG, AC4 and AC10) are presented in table 2. The time spent sedentary is significantly (p-value < 0.05) higher with AG than AC4 and AC10. The time spent within the light intensity domain is significantly ($p < 0.05$) increased with both AC4 and AC10 as compared to AG and this is consistent across both regression and ROC based cut-points. The time spent within the moderate intensity domain estimated with the ROC generated cut-points (ROCI and ROCII) is substantially lower than estimated with the cut-points generated with regression. There is a small but significant ($p < 0.05$) increase of the moderate intensity domain with AG compared to AC4 and AC10 with three of the cut-points. Only the REGIII cut-points provide a time within moderate that demonstrates a similar or increased time with AC4 and AC10 compared to AG. The time spent vigorously range from 7.2-18.1 minutes. There is a significant ($p < 0.05$) increased time spent vigorously with AG compared to AC4 and AC10 with four of the six cut-points (REGI, REGII, REGIII and ROCI), while the is instead a significant ($p < 0.05$) increased time with AC4 and AC10 compared to AG with REGIV and ROCII.

Discussion

This is the first study to investigate the measurement bias with AG counts and effect of alternative band-pass filters during walking and running and during free-living. The counts output with all band-pass filters demonstrate a positive linear association during walking for all age groups and negative during running for AG, whereas positive associations were found with AC10. A positive association during running was also observed with AC4 although not with children. This could be attributed to the use of a small indoor gym and the consequence of increased number of turns with running speed, but also a lack of the children to sustain high speed running. The AG counts obtained in this study during locomotion is consistent with previous studies demonstrating the plateau effect or inverted-U phenomenon above 10 $km \cdot h^{-1}$ (Brage, Wedderkopp, Franks, Andersen & Froberg 2003). Considering higher frequency information in the generation of counts reduce the measurement bias with running at speeds above 10 $km \cdot h^{-1}$ and supports the proposed hypothesis that the plateau phenomenon is caused by the narrow band-pass filter (John, Miller, Kozey-Keadle, Caldwell & Freedson 2012). However, estimated free-living VPA was similar or lower with AC4 and AC10 as compared to AG with four of the six generated cut-point sets. This finding was not expected and in strong contrast to the proposed hypothesis.

REGIV and ROCII were the only set of cut-points to demonstrate an increased free-living VPA with AC4 and AC10 counts as compared to AG counts. The estimation of these cut-points did not include the running activity from the calibration protocol. Excluding the running activity to provide an increased VPA with AC4 and AC10 as compared to AG, seems to be required by the elevated counts output with AC4 and AC10 during running as compared to walking, which is not demonstrated with AG counts. Increasing the frequency information from 1.66Hz to >4Hz in the generation of counts tend to favor running more than walking, which is caused by the difference in step frequency with the two locomotion types. The step frequency of walking is below 2Hz whereas step frequency for running is above 3Hz (Schepens*, et al.* 2004; Schepens*, et al.* 1998). This seems to indicate that extending the consideration of frequencies provides a counts output during locomotion that tend to be more in line with biomechanics per se and specifically the substantial higher peak ground reaction force observed with running as compared to walking (Keller*, et al.* 1996).

The purpose of the narrow band-pass filter originally implemented in the AG counts processing was to reduce the influence of external noise (Tryon & Williams 1996). However, considering the counts generated using the AC4 and AC10 band-pass filters during running as compared to walking it seems to suggest that the original band-pass filter is also implemented as an important prerequisite. The effect of the original band-pass filter clearly reduce the influence of locomotion type with the association between locomotion speed and AG counts and thus demonstrates the same association as EE (METs) with locomotion speeds (Ainsworth*, et al.* 2011).

The strong focus on cyclic movements and specifically running with the inclusion of higher frequency information could potentially have a negative consequence for the accurate identification of intermittent activities as VPA. Most intermittent game based activities performed by children and adolescents are considered VPA (Butte*, et al.* 2018) and the proportion of the basketball activity performed in the calibration experiment to be identified as VPA from the different cut-points is almost non-existing with AC4 (<1.4%) and AC10 (<3.5%) as compared to AG (<23%). Thus, the increased time identified in VPA with AG counts as compared to AC4 and AC10 counts is most likely explained by, that the suppression of vigorous activity with the AG filter will erroneously force down the cut-point for VPA and thereby accidentally include more intermittent activities as VPA. It has been demonstrated that the estimated intensity of intermittent activities from hip worn accelerometry using AG counts is biased (Staudenmayer, *et al.* 2012). Therefore, an improved assessment of free-living VPA needs to consider accurate intensity assessment of intermittent activities in addition to target the measurement bias with running speeds higher than $10 km \cdot h^{-1}$.

Conclusions

Extending the frequency range with the generation of ActiGraph counts reduces the measurement bias with running activities above $10 km \cdot h^{-1}$. However, contrary to our expectations, there was no increase in free-living VPA compared to the original ActiGraph counts. The original band-pass filter implemented with AG counts still provides the most optimal solution for the assessment of VPA when using cut-points predicted from ROC and regression analysis. The processing of raw acceleration into counts also needs to be developed to capture intermittent activity for an increase in vigorous activity would be detectable compared with the original ActiGraph counts.

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Competing interests

The authors have no conflict of interests that have influenced the work.

Figure caption

Figure 1. The frequency response indicated by the spectral density power (Decibel) of the original AG, and the AC4 and AC10 band-pass filters.

Figure 2. Linear regression analysis of the relationship between locomotion speed and aggregated counts data with the different band-pass filters in adults (A), adolescents (B) and children (C).

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Table 1. Method specific cut-points generated from both ROC and regression analysis. The sensitivity and specificity is provided with the cut-points from the ROC analysis.

	Moderate			Vigorous		
	AG	AC4	AC10	AG	AC4	AC10
Regression I	2051	15211	17491	5783	57627	66708
Regression II	1972	13996	16645	4900	43663	51242
Regression III	2161	14737	17511	6018	56609	65782
Regression IV	2016	14059	16591	6250	43967	51767
ROC I	3648	24403	28623	5765	51525	58963
ROC II	4288	26121	29817	6309	44195	49152

Table 2. Minutes spent in different intensity domains by aggregation and analytical method used to generate the cut-point thresholds.

Regression		**Sedentary**	**Light**	**Moderate**	**>Vigorous**
I	**AG**	507.8 (59.6)	197.6 (35.3)	65.9 (21.0)	12.3 (9.7)
	AC4	467.1 (59.3)*	251.7 (43.8)*	60.5 (20.7)*	7.2 (5.9)*
	AC10	463.7 (59.6)*	256.2 (44.4)**	63.2 (21.2)**	7.9 (5.7)*
II	**AG**		194.5 (34.7)	63.2 (19.3)	18.1 (11.6)
	AC4		245.2 (42.6)*	61.1 (19.6)*	13.0 (8.6)*
	AC10		249.9 (43.3)**	63.6 (20.1)***	13.9 (8.6)*
III	**AG**		202.0 (36.1)	62.7 (20.6)	11.2 (9.3)
	AC4		249.2 (43.4)*	62.6 (21.1)	7.5 (6.1)*
	AC10		254.2 (44.0)**	65.0 (21.5)***	8.2 (5.9)*
IV	**AG**		196.2 (35.0)	69.4 (22.2)	10.3 (9.0)
	AC4		245.6 (42.7)*	60.9 (19.6)*	12.9 (8.6)*
	AC10		249.6 (43.3)**	64.2 (20.2)**	13.6 (8.5)*
ROC					
I	**AG**		241.8 (43.9)	21.7 (9.4)	12.4 (9.7)
	AC4		283.7 (49.2)*	26.3 (11.1)*	9.3 (6.9)*
	AC10		290.4 (50.1)**	26.5 (10.8)*	10.5 (7.0)**
II	**AG**		251.4 (45.9)	14.4 (7.0)	10.1 (8.9)
	AC4		287.4 (49.9)*	19.2 (8.1)*	12.7 (8.5)*
	AC10		292.7 (50.5)**	19.7 (7.9)*	15.0 (9.1)**

* Significant different from AG (P<.05)
** Significant different from AG and AC4 (P<.05)
*** Significant different from AC4 (P<.05)

Figure 1

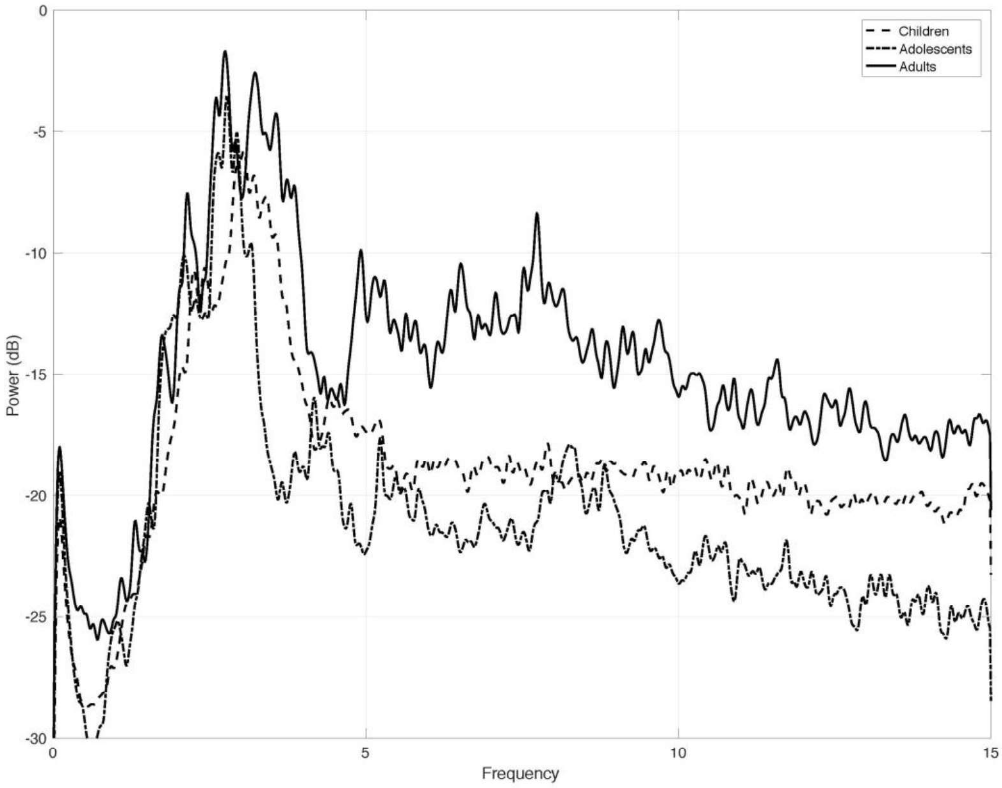
Children
Adolescents
Adults
Power (dB)
Frequency
0
-5
-10
-15
-20
-25
-30
0
5
10
15

Figure 2

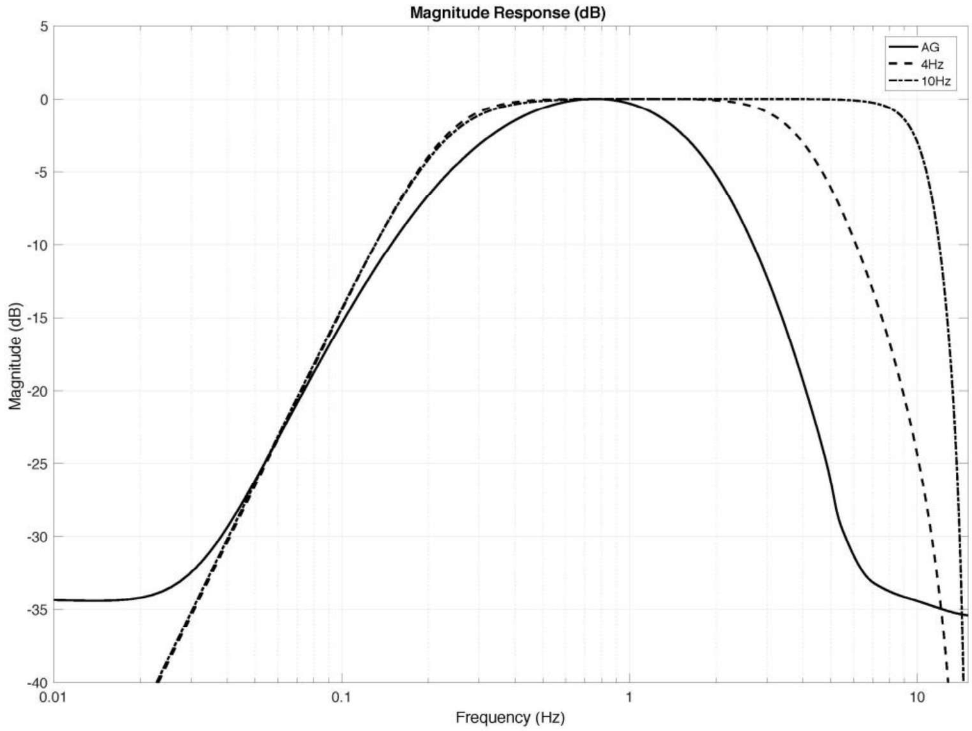

Figure 2

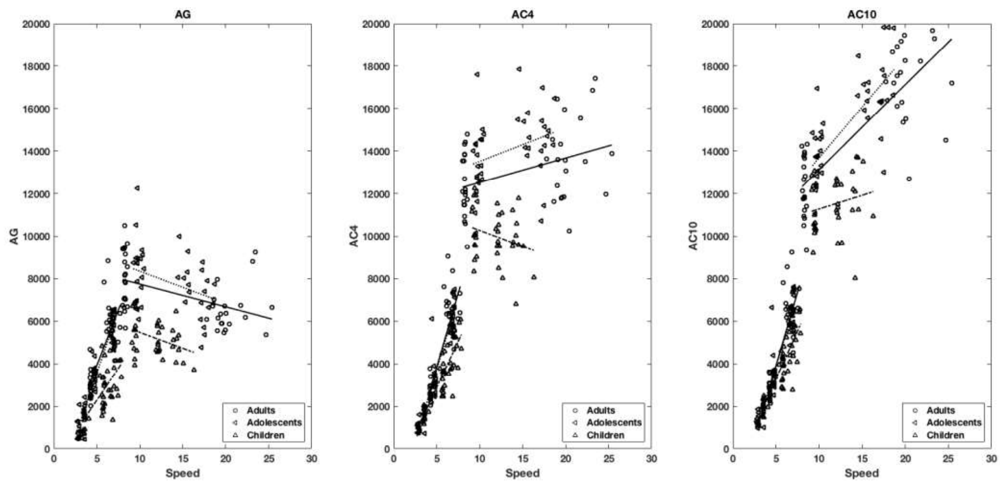

Figure 3