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Machine learning to quantify habitual physical activity in children with cerebral palsy

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ABBREVIATION

SVM Support vector machine

[Abstract]

AIM To investigate whether activity-monitors and machine learning models could provide accurate information about physical activity performed by children and adolescents with cerebral palsy (CP) who use mobility aids for ambulation.

METHOD Eleven participants (mean age 11y [SD 3y]; six females, five males) classified in Gross Motor Function Classification System (GMFCS) levels III and IV, completed six physical activity trials wearing a tri-axial accelerometer on the wrist, hip, and thigh. Trials included supine rest, upper-limb task, walking, wheelchair propulsion, and cycling. Three supervised learning algorithms (decision tree, support vector machine [SVM], random forest) were trained on features in the raw-acceleration signal. Model-performance was evaluated using leave-one-subject-out cross-validation accuracy.

RESULTS Cross-validation accuracy for the single-placement models ranged from 59% to 79%, with the best performance achieved by the random forest wrist model (79%). Combining features from two or more accelerometer placements significantly improved classification accuracy. The random forest wrist and hip model achieved an overall accuracy of 92%, while the SVM wrist, hip, and thigh model achieved an overall accuracy of 90%.

INTERPRETATION Models trained on features in the raw-acceleration signal may provide accurate recognition of clinically relevant physical activity behaviours in children and adolescents with CP who use mobility aids for ambulation in a controlled setting.

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Machine Learning and Physical Activity in CP *Benjamin I Goodlich et al.*

What this paper adds:

- Machine learning may assist clinicians in evaluating the efficacy of surgical and therapy-based interventions.
- Machine learning may help researchers better understand the short- and long-term benefits of physical activity for children with more severe motor impairments.

[main text]

Children with cerebral palsy (CP) tend to engage in less physical activity than their typically developing peers, which can negatively influence their musculoskeletal development, and predispose them to lifestyle related conditions such as obesity and cardiovascular disease.[1–4] Generally, physical activity participation is higher among ambulant children with CP, and declines as Gross Motor Function Classification System (GMFCS) level increases.[4] In particular, children classified in GMFCS levels III and IV have been reported to be at an increased risk of experiencing a clinically significant functional decline with age, as measured by the 66-item version of the Gross Motor Function Measure.[4] Consequently, therapeutic interventions for these children, who ambulate using a mobility device, often target increased levels of physical activity.[5–7] Accurate measurement of physical activity levels in these children is therefore important, as it can guide therapist treatment selection, progression, and establish treatment efficacy.

Accelerometers are widely accepted as the best method to objectively measure physical activity in children across both typically developing and CP populations.[8] Traditionally, intensity-based thresholds known as ‘cut-points’ have been used to categorize pre-processed accelerometer data (activity counts) as sedentary, light physical activity, or moderate-to-vigorous physical activity.[9,10] Cut-point thresholds are identified by collecting energy expenditure, using indirect calorimetry, and accelerometer data concurrently during standardized activity trials. However, such trials typically involve walking at various speeds; an activity which precludes the participation of those in GMFCS level IV and minimizes the participation of participants in GMFCS level III. To date, a number of studies have derived CP-specific cut-points[10–14] and this has subsequently enabled researchers to gain broad insight into the physical activity behaviours of children with CP. However, the cut-point method has several limitations as evidenced by the considerable variation in published intensity-related cut-point thresholds between different authors and research groups, particularly when applied to participants with more severe motor impairments.[15] CP-specific cut-point thresholds were initially developed across the spectrum of GMFCS levels as a ‘one size fits all’ approach.[10] These broad cut-points have been shown to misclassify the intensity of 40% of light physical activity trials and 30% of moderate-to-vigorous physical activity trials in participants in GMFCS level III.[14] Substantial improvements have been reported with the development of GMFCS level specific cut-points though misclassification rates were still high when investigating a GMFCS level III population (11–17% and 10–11% for light physical activity and moderate-to-vigorous physical activity respectively).[14] A further limitation to this methodology is that cut-point methods do not consider physical activity type, and therefore has shortcomings when evaluating intervention efficacy. Identifying which types of physical activities have increased or decreased after intervention may provide the clinician with a more objective view of patients' habitual physical activities. Consequently, there is a clear need to explore alternative methods when investigating children with CP with more severe motor impairments such as those classified in GMFCS levels III and IV.

Pattern recognition methodologies, such as machine learning approaches, have the potential to improve the accuracy of habitual physical activity assessments in children with CP.[16] Machine learning involves the extraction of informative features from data and entering them into statistical algorithms which model underlying relationships in order to make predictions. Among typically developing children, machine learning algorithms such as random forest, support vector machine (SVM), and logistic regression have been used to process data from wearable sensors, providing accurate predictions of physical activity type and measurements of physical activity intensity, with accuracy ranging from 78% to 91%.[8,16,17] Comparable prediction accuracies were reported in a recent study of children with CP.[18] Features from a single accelerometer at the hip and wrist achieved 83% to 86% and 76% to 83% accuracy classifying activity type. When features from these two placements were combined, further improvements in classification accuracy were observed (86–89%). Although this study demonstrated that machine learning approaches were feasible and had the capacity to advance the measurement of physical activity in children with CP, it included very few participants in GMFCS level III and none in GMFCS level IV. As such, there are no methods available for this patient group and hence measures of physical activity that are validated for other groups may be inaccurate. To our knowledge, no previous study has evaluated the validity of machine learning methods to classify physical activity type in children and adolescents with CP, in GMFCS level IV. Filling this gap is a critical step towards individualizing therapies to the specific needs of this patient group (children with CP, in GMFCS levels III and IV), particularly in the context of important activities of daily living such as transfers (e.g. from wheelchair to bed, sitting to standing in a walking frame), wheelchair use, and upper-limb activity.

The purpose of this study was to develop and test machine learning algorithms to classify physical activity type in children with CP with more severe motor impairments (GMFCS levels III and IV). To determine the effects of accelerometer placement on the accuracy of predictions of physical activity type, we compared models trained on accelerometer data collected on the wrist, hip, thigh, and all two- and three-placement combinations. We hypothesized that data from single accelerometers worn on the hip, thigh, and wrist could classify activity type, and that a combination of data from multiple accelerometers would significantly improve classification accuracy.

METHOD

Participants

Children and adolescents with CP who were enrolled in an intervention study[19] at the Queensland Children's Hospital were invited to participate in this methodological study. Participants were included if they: (1) had a confirmed diagnosis of CP; (2) were classified in GMFCS levels III or IV; (3) were aged 6 to 18 years; (4) used a mobility aid for ambulation; (5) had adequate cognition and attention to follow instructions. Participants were excluded if they had: (1) a recent musculoskeletal injury; (2) orthopaedic surgery within the previous 12 months and did not have medical clearance to participate; (3) uncontrolled epilepsy; (4) cardiac condition; (5) uncontrolled asthma. Written informed consent was obtained from parents and/or guardians and assent from participants if they were 12 years or older. Ethical approval was obtained from Griffith University (2018/037) and the Children's Health Queensland Hospital and Health Service Human Research Ethics Committee (HREC/17/QRCH/88).

Data collection

The study design included six standardized activity trials. Participants completed activity trials while wearing ActiGraph GT3X+ tri-axial accelerometers (ActiGraph Corporation, Pensacola, FL, USA) placed dorsally on the wrist over the capitate bone, on the hip superior to the iliac crest in the mid-axillary line, and anteriorly on the mid-thigh. All accelerometers were fixed using either adhesive tape or an elastic belt and were placed on the participant's least affected side.[9] If the participant did not have a least affected side, then the accelerometers were placed on their dominant side (i.e. the side used to colour or throw). Activity trials were completed in a single 60- to 90-minute session and comprised the following activities: (1) supine rest, (2) colouring, (3) ball throwing and catching, (4) overground walking with a mobility aid, (5) wheelchair propulsion, and (6) cycling on a modified tricycle. Descriptions for each activity are detailed in Table 1. The walking, wheelchair propulsion, and cycling activity trials were conducted in a 30m hallway, with cones demarcating the turning points. Participants were encouraged to complete the activities as they usually would at home or school, including the use of their usual mobility aids or assistive devices. Activity trials were 5 minutes in duration and were selected to simulate repetitive activities, typical of children who use walkers and/or wheelchairs. All activities were completed under the direct observation of two investigators, and video footage of activity trials was also collected. Participants were not required to attempt activity trials that were not applicable to them (e.g. a child who ambulated with a walker was not required to perform wheelchair propulsion and vice versa).

Data pre-processing and feature extraction

A sampling frequency of 30Hz was used to measure raw-accelerations in the vertical, medial-lateral, and anterior-posterior planes. Each activity trial was timestamped so that the relevant 5 minutes could be identified, from which the first and final minutes were removed. The purpose of this was to be able to process the acceleration signal for the middle 3 minutes of continuous activity. The acceleration signal from each axis was transformed into a single dimension vector magnitude using the equation:

$$vector\ magnitude = \sqrt{(x^2 + y^2 + z^2)}$$

A total of 40 features, shown to be beneficial in previous activity recognition studies involving typically developing children and children with CP, were extracted from the vector magnitude over 5 second non-overlapping windows.[17,18] The selected time domain features were as follows: mean, standard deviation, coefficient of variation, centiles (10th, 25th, 50th, 75th, 90th), skewness, kurtosis, maximum, minimum, peak to peak, median crossings, zero crossings, sum, mean absolute deviation, power, lag-1 autocorrelation, log energy, interquartile range, cross-axis correlations (yz, yx, xz), as well as four activity fragmentation features, which are described elsewhere.[17] The selected frequency domain features included dominant frequency between 0.25Hz to 5Hz and dominant frequency magnitude between 0.25Hz to 5Hz. Selected angular/rotation features (orientation measurements of the accelerometer) included mean tilt, roll, and pitch.

Model training and cross-validation

Three supervised learning algorithms were used to develop the activity classification models: decision tree, random forest, and SVM. Detailed descriptions of these algorithms can be found elsewhere.[20–22] The random forest models were built with 500 trees and the number of features randomly sampled at each split was six. For the SVM models, the cost parameter was optimized at 1.0. Colouring and throwing were combined into a single 'upper-limb' class to represent seated upper-limb tasks typical of children who spend the vast majority of their day in a chair. Minimum Redundancy Maximum Relevance feature selection[23] was employed to identify the most pertinent features. Models were trained and cross-validated using the 'kernlab', 'randomForest', 'rpart' functions within the 'caret' package within R (version 3.3.2; R Foundation for Statistical Computing, Vienna, Austria).[24] Models were trained on features from a single accelerometer placement, and the combination of data from two and three placements. Model-performance was evaluated using leave-one-subject-out cross-validation. The model is trained on data from all participants except one, which is omitted from training and used as a test data set. This process is repeated until each participant has been the hold out. Model-performance was evaluated using overall accuracy and *F* scores.

Overall accuracy was calculated as:

$$\frac{correctly\ classified\ observations}{total\ observations} \times 100$$

F score was calculated as:

$$\frac{(2 \times Precision \times Recall)}{(Precision + Recall)} \times 100$$

Overall accuracy was calculated for each classifier (random forest, decision tree, SVM) and combination of accelerometer placement (i.e. seven different combinations) – producing 21 different classification accuracies in total. Confusion matrices, which compare predicted observations to the actual observation, were generated to summarize trends of misclassification for each of the models developed.

Statistical analysis

Performance differences for the best single-, two-, and three-placement models were tested for statistical significance using one-way repeated measures analysis of variance (ANOVA) using SPSS statistical software (Version 24; IBM Corp., Armonk, NY, USA). Before running the repeated measures ANOVA, the data was checked for outliers, normality, and sphericity. Pairwise comparisons were assessed using Bonferroni post hoc analysis. When analysing the confusion matrices, classification accuracies were considered as greater than 80% indicating ‘excellent’, 71% to 80% ‘good’, 51% to 70% ‘fair’ and less than 50% ‘poor’.

RESULTS

This study included 11 participants (six females, five males; five GMFCS level III, six GMFCS level IV). The mean age was 11 years (SD 3y), height 1.35m (SD 0.17m), and weight 41.22kg (SD 8.12kg). Ten participants had spastic CP, and one had dystonic CP. All participants had bilateral distribution of affects (six diplegic and five quadriplegic).

Cross-validation recognition accuracy for the single-placement, two-placement, and three-placement models are reported in Table 2. The best performing single-placement model was a random forest classifier trained on wrist features, yielding an overall classification accuracy of 79%. The best performing model developed on a combination of two placements was a random forest classifier trained on wrist and hip features, yielding an overall classification accuracy of 92%. Of the models developed on a combination of all three placements, an SVM classifier was most effective, producing an overall classification accuracy of 90%. The classification accuracy for three best performing models are presented in Figure 1. A one-way repeated measures ANOVA was conducted to determine whether the combination of two or three accelerometers improved physical activity type classification accuracy using results from the best performing placement/machine learning model for each. The data were normally distributed at each time point, as assessed by Shapiro–Wilk test

($p>0.05$). There was a statistically significant effect for placement ($F_{2,20}=16.5$, $p<0.001$). Post hoc analysis with a Bonferroni adjustment revealed that the combination of multiple accelerometer placements (wrist and hip or wrist, hip, and thigh) exhibited statistically significantly higher accuracy than a single monitor alone ($p<0.05$), but there was no difference between placement of two or three monitors ($p=1.00$).

Confusion matrices for the best performing single-placement and two- and three-placement models are presented in Tables 3, 4, and 5 respectively. Activity recognition ranged from good to excellent for supine rest (80–100%), good to excellent for wheelchair propulsion (77–85%), good to excellent for walking (79–97%), and excellent for upper-limb tasks (88–94%). Classification accuracy for cycling was poor using a wrist classifier (46%) but improved using a combination of hip and wrist (73%). Recognition of cycling was highest using a combination of all three placements (80%).

DISCUSSION

To our knowledge, this is the first study to develop and test machine learning models to classify physical activity type in children and adolescents with CP who rely on mobility aids for ambulation. Classifiers in this study, trained on features from the vector magnitude of raw-acceleration signal from the wrist, hip, thigh, and combinations of these placements, achieved good to excellent recognition accuracy for a range of physical activities commonly performed by children with CP, in GMFCS levels III and IV. Furthermore, the classifiers could detect and classify both seated and standing activity, as well as upper-limb involvement during seated activities and wheelchair propulsion. In the context of children with CP classified in GMFCS levels III and IV this is a significant finding. These specific movements encompass the diversity of mobility in this population, as well as the functional requirements to participate in a range of activities at school and at home. The classifiers developed in this study achieved comparable accuracy to those trained in both typically developing children and ambulatory children with CP.[8,16,18,25,26]

The overall accuracy of classifiers trained on data from a single accelerometer was variable, ranging from 59% to 79%. The most accurate model trained on data from a single placement was a random forest classifier trained on wrist data. Inspection of the confusion matrix for this classifier reveals prediction accuracies greater than 79% for all classes of activity except cycling. This is a logical finding when considering the upper-limb requirements of most tasks assessed in this study (ball throwing, colouring, wheelchair propulsion), and the accurate recognition of supine class irrespective of accelerometer placement. These results support the use of a single accelerometer placed at the wrist to measure habitual physical activity in a clinical scenario where cycling is not an activity of interest, and wearing multiple accelerometers is not feasible.

In agreement with our hypothesis, the overall accuracy of classifiers trained on data from a combination of accelerometers was significantly higher than classifiers trained on data from a single placement. However, there was no significant increase in accuracy when comparing a combination of two placements and three placements. This finding corroborates the results of a previous study in typically developing adults, where significant improvements in classification accuracy were observed with the increase of sensing locations from one to two or more sensors, yet no further improvement was observed with the addition of data from more than two locations.[27] Results from this study add further support to the notion that accurate activity detection can be achieved with only two accelerometers, depending on the placement and activity type being investigated.

Consistent with results of studies conducted in typically developing children[16] and ambulant children with CP,[18] the combined hip and wrist classifier achieved consistently higher overall accuracies than the single-placement classifiers. In these studies, however, the difference in accuracy between a single placement and a combination of placements was small, suggesting little clinical benefit. In the present study, the difference was considerably greater and likely to be of clinical relevance. Improved physical activity classification with the application of two accelerometers on the wrist and hip may enable researchers and clinicians to better tailor interventions to the specific needs of children and adolescents with CP classified in GMFCS levels III and IV. This finding is particularly important considering activities of daily living for this population such as transfers (e.g. wheelchair to bed, sitting to standing in a walking frame), wheelchair use, and upper-limb activity. The fusion of features from multiple sites may improve activity detection and classification across a range of tasks by nullifying the weaknesses that one sensor location may have for detecting certain movements.[18] The result is an algorithm which is robust enough to produce accurate classifications in the context of variable movement patterns present when quantifying habitual physical activity in children with CP in GMFCS levels III and IV.

Results from this study support the use of accelerometers and machine learning approaches to classify physical activity. In particular, accurate recognition of supine rest was achieved across different sensor placement locations and combinations of sensor placements. This finding is of significance in the context of increased emphasis on reducing sedentary time in conjunction with changes to habitual physical activity.[5,28] Accurate classification of physical activity type may assist clinicians in gaining a clear picture of habitual activity *and* sedentary behaviour, and allow researchers to accurately track the impact of interventions in terms of participation in different physical activities.

During the activity trials, significant encouragement was required for some participants to tolerate wearing three activity-monitors for the full 60- to 90-minute session. The variability in children's level of tolerance and willingness to follow instructions can likely be attributed to the range of associated conditions that were present in the study cohort, including intellectual disability (*n*=5), sensory processing difficulties (*n*=1), and behavioural disorders (*n*=2). The decision to not exclude children with associated conditions was considered necessary to achieve a study sample that emulates the wider population of people with CP, whereby one in two children have an intellectual disability and one in four have behaviour problems.[29,30] A further explanation for the variability in tolerance was that the study included children as young as 6 years old, who were not motivated by the study objectives and required encouragement to keep the monitors on for the duration of the activity trials. Such factors are important for clinicians to consider when prescribing wearable devices to track habitual physical activity in children with CP in the community, where constant supervision is not feasible and data collection spans over a period of days rather than hours.

The present study had several limitations that should be acknowledged. First, all classifiers were trained and tested using acceleration data collected in a clinical environment and included controlled activity trials which may not be representative of activity patterns in free-living conditions. Accordingly, additional testing of these classifiers on data collected in a free-living environment is required to evaluate generalizability. Second, models were trained on a relatively small number of participants and hence may not generalize to all children in GMFCS levels III and IV – which is heterogenous with respect to impairment and movement behaviours. Finally, walking, wheelchair propulsion, and cycling trials were all performed indoors in a clinical setting and not in the real world with varying incline/decline.

Conclusion

This study developed machine learning physical activity classification models for children and adolescents with CP who rely on mobility aids for ambulation. In this study, classifiers trained on accelerometer features from the wrist, hip, thigh, and combinations of these placements were used to accurately detect physical activity type in children in GMFCS levels III and IV. The combination of accelerometer features from the wrist and hip yielded the best overall classification accuracy. Future studies investigating children and adolescents with CP in GMFCS levels III and IV can use these population specific classifiers to evaluate the efficacy of interventions.

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[Figure legend]

Figure 1: Overall accuracy of the best performing single-placement activity-monitor, combination of two- and three-placement classifiers. Error bars indicate standard error. [a]Indicates significantly different from wrist (p<0.05).

Table 1: Physical activity trial descriptions

Activity	Description
1. Supine rest	Participants were instructed to lay down and rest, but not to sleep.
2. Colouring	In a seated position (chair or wheelchair if appropriate), participants used their dominant hand to colour a picture of their choice.
3. Ball throwing and catching	In a seated position, participants threw a ball to a therapist, who returned the ball, and this was repeated.
4. Overground walking with a mobility aid	Participants used their regular mobility aid to walk at a brisk pace: 'as if you're hurrying to get to class on time'. The pace was self-selected by the child.
5. Wheelchair propulsion	Participants manually propelled their wheelchair.
6. Cycling on a modified tricycle	Participants cycled using an adapted tricycle or recumbent bike.

Table 2: Cross-validation accuracies and *F* scores

Activity-monitor placement	**Overall accuracy % (*F* score)**		
	Support vector machine	Random forest	Decision tree
Wrist	77.3 (74.1)	79.0 (76.5)	76.6 (72.8)
Hip	65.6 (63.5)	65.4 (63.1)	61.6 (60.8)
Thigh	65.6 (63.3)	62.4 (60.1)	59.0 (57.7)
Wrist + hip	89.0 (88.6)	91.9 (91.2)	86.5 (86.1)
Wrist + thigh	88.5 (87.9)	89.8 (89.5)	76.4 (76.0)
Hip + thigh	74.7 (74.2)	76.2 (75.6)	70.2 (69.8)
Wrist + hip + thigh	90.4 (89.2)	88.2 (87.1)	84.0 (83.4)

Table 3: Confusion matrix for random forest classifier trained on wrist data

			Prediction		
Observed	Supine	WC	Cycle	Walk	UL
Supine	**447 (0.80)**	5 (0.01)	35 (0.17)	2 (0.01)	24 (0.04)
WC	0 (0.00)	**285 (0.81)**	1 (0.01)	33 (0.15)	24 (0.04)
Cycle	25 (0.05)	0 (0.00)	**91 (0.46)**	0 (0.00)	21 (0.03)
Walk	0 (0.00)	12 (0.03)	0 (0.00)	**172 (0.79)**	9 (0.01)
UL	85 (0.15)	52 (0.15)	70 (0.36)	11 (0.05)	**552 (0.88)**

Numbers represent observation counts, % of observations for a given class are reported in brackets. Values in bold indicate number and proportion of correctly classified observations. WC, wheelchair propulsion; UL, upper-limb task.

Table 4: Confusion matrix for random forest classifier trained on wrist and hip data

	Prediction				
Observed	Supine	WC	Cycle	Walk	UL
Supine	**557 (1.00)**	0 (0.00)	0 (0.00)	1 (0.01)	8 (0.01)
WC	0 (0.00)	**301 (0.85)**	0 (0.00)	5 (0.02)	26 (0.04)
Cycle	0 (0.00)	0 (0.00)	**144 (0.73)**	0 (0.00)	0 (0.00)
Walk	0 (0.00)	0 (0.00)	5 (0.03)	**209 (0.96)**	0 (0.00)
UL	0 (0.00)	52 (0.15)	48 (0.24)	3 (0.01)	**590 (0.94)**

Numbers represent observation counts, % of observations for a given class are reported in brackets. Values in bold indicate number and proportion of correctly classified observations. WC, wheelchair propulsion; UL, upper-limb task.

Table 5: Confusion matrix for support vector machine classifier trained on wrist, hip, and thigh data

	Prediction				
Observed	Supine	WC	Cycle	Walk	UL
Supine	**551 (0.99)**	0 (0.00)	0 (0.00)	0 (0.00)	5 (0.01)
WC	0 (0.00)	**274 (0.77)**	0 (0.00)	0 (0.00)	39 (0.06)
Cycle	0 (0.00)	0 (0.00)	**157 (0.80)**	0 (0.00)	1 (0.00)
Walk	0 (0.00)	2 (0.01)	16 (0.08)	**211 (0.97)**	10 (0.02)
UL	6 (0.01)	78 (0.22)	24 (0.12)	7 (0.03)	**575 (0.91)**

Numbers represent observation counts, % of observations for a given class are reported in brackets. Values in bold indicate number and proportion of correctly classified observations. WC, wheelchair propulsion; UL, upper-limb task.