Published in final edited form as:

J Autism Dev Disord. 2018 May ; 48(5): 1458–1466. doi:10.1007/s10803-017-3408-6.

Automated detection of repetitive motor behaviors as an outcome measurement in intellectual and developmental disabilities

Kristin H. Gilchrist^a, Meghan Hegarty-Craver^a, Robert B. Christian^b, Sonia Grego^a, Ashley C. Kies^b, and Anne C. Wheeler^a

^aRTI International, Research Triangle Park, NC

^bCarolina Institute for Developmental Disabilities, University of North Carolina, Chapel Hill, NC

Abstract

Repetitive sensory motor behaviors are a direct target for clinical treatment and a potential treatment endpoint for individuals with intellectual or developmental disabilities. By removing the burden associated with video annotation or direct observation, automated detection of stereotypy would allow for longer term monitoring in ecologic settings. We report automated detection of common stereotypical motor movements using commercially available accelerometers affixed to the body and a generalizable detection algorithm. The method achieved a sensitivity of 80% for body rocking and 93% for hand flapping without individualized algorithm training or foreknowledge of subject's specific movements. This approach is well-suited for implementation in a continuous monitoring system outside of a clinical setting.

Keywords

Accelerometer; Wearable sensor; Motor stereotypy; Repetitive behaviors; Activity recognition; Neurodevelopmental disorders

Repetitive sensory motor behaviors (RSM), including body rocking, complex hand and finger movement, and hand flapping, are common among individuals with intellectual or developmental disabilities (IDD), and are part of the core features of autism spectrum disorders (ASD). Often associated with sensory seeking (Boyd et al. 2010), these RSMs are sometimes referred to as the “lower-level” forms of restricted and repetitive behaviors (RRBs), as a contrast to the higher-order restricted interests and insistence for sameness also included in the diagnostic category of RRBs. Unlike the “higher-order” behaviors however, most children, including those whose development is typical, will engage at some point in

Corresponding author: Kristin H. Gilchrist, RTI International, 3040 E. Cornwallis Road, Research Triangle Park, NC 27709, kgilchrist@rti.org, 919-248-1456.

Note: Ashley Kies affiliation has changed subsequent to the time of the study. Her current affiliation is: Child and Family Development, Inc., Charlotte, NC

Compliance with Ethical Standards:

Conflict of Interest: All authors declare that they have no conflicts of interest.

Informed consent: Informed consent was obtained from all individual participants included in the study.

motor stereotypes. Indeed, repetitive motor movements are considered a component of normal development, enhancing muscular control and promoting neural and cognitive development (Eilam et al. 2006; Hoch et al. 2016). However, for individuals with neurodevelopmental disorders, these behaviors often do not resolve and ultimately become dysfunctional. In these cases, RSMs may be associated with poorer adaptive behavior (Bishop et al. 2006), restrictions in activities (Bodfish et al. 2000; Lewis 2004), challenges with social relationships (Loftin et al. 2008; Nadig et al. 2010), disruptions to learning (Pierce and Courchesne 2001), social stigmatization and poorer quality of life (Bodfish et al. 2000), in addition to having a negative effect on family members (Bishop et al. 2007; Harrop et al. 2014; Lounds et al. 2007; Shattuck et al. 2007). It has also been suggested that RSMs can be precursors to more serious acts of aggression and/or self-injurious behaviors (Oliver et al. 2012). Because RSMs are common and sometimes associated with distress, they have been considered not only a direct target for clinical treatment (Boyd et al. 2012; Carrasco et al. 2012; Rapp and Vollmer 2005), but also a potential treatment endpoint for clinical trials targeting irritability in autism and other IDD populations (McCracken et al. 2010; Berry-Kravis et al. 2013).

There are concerns regarding the most appropriate tool to measure repetitive behaviors as a treatment endpoint (Scahill et al. 2015). Pen and paper tools and manual behavioral coding software packages have been the mainstay of measuring behaviors in clinical research and institutional settings (Aman et al. 1985; Matson and Minshawi 2007; Matson et al. 2006). Because prolonged direct observation may not be practical in some real-world settings, such as home and school, such data collection rarely takes place, leaving clinicians to make decisions based on informal parent or teacher reports which are often subject to bias. Emerging methods for behavioral observations based on discontinuous measurements, such as momentary time sampling (MTS) (Devine et al. 2011) offer promise for reducing this burden. Such discontinuous measurement methods are preferred by therapists for their practical convenience (Kolt and Rapp 2014), however further research is needed to assess the accuracy and sensitivity of the methods in relation to the specific selection of sampling time and event-related parameters (Wirth et al. 2014). A system enabling automated detection of behaviors for continuous duration recording has the potential for refined detection of behavior changes while remaining convenient for practitioners and complementing MTS methods for improved assessments.

The rapid growth and development of wearable sensors offers new and transformative ways to better track human behavior in natural settings in an unobtrusive way, however to date no commercial solutions exist for tracking stereotypical motor behaviors. A few research groups have carried out investigations using accelerometers and algorithms to detect repetitive movement and self-injurious behavior (Albinali et al. 2012; Goodwin et al. 2011; Rodrigues et al. 2013; Plotz et al. 2012). Plotz et al., demonstrated a system for detection of problem behaviors in a single case study which showed promise for detecting some of these behaviors, but highlighted the difficulty in detecting a wide range of behaviors with minimal sensor burden (Plotz et al. 2012). Goodwin and colleagues presented an approach using automated pattern recognition to detect rocking and flapping (Albinali et al. 2012; Goodwin et al. 2011). While the algorithm performed well when trained on previous data for a specific individual, it was not generalizable. Additionally, the algorithm was developed and tested on

seated participants, so it is unclear how well the algorithm would perform in a natural setting with freely moving subjects. Rodrigues et al., reported a method for detection of hand flapping with accelerometers on each wrist, but the algorithm suffered from a high rate of false positives.

The goal of this work was to demonstrate the feasibility of robust algorithmic detection of common stereotypical motor movements based on a generalized strategy that does not require algorithm training or foreknowledge of subject's specific movements. We used compact accelerometers affixed to the wrists and torso to record movement and an algorithm to automatically detect and classify the most common repetitive behaviors, hand flapping and body rocking. In order to develop a tool with practical utility for behavior research and clinical studies, we used commercially available accelerometers with a small size to maximize comfort of the users. We placed multiple accelerometers to determine the minimum number and placement of sensors required for detection. While the approach was demonstrated on behaviors recorded in a clinical setting, the technology is amenable to implementation in a system suitable for home use.

Methods

Participants

Data was collected on 20 subjects in an IRB approved study. Participants were recruited from a research registry of individuals with autism or related developmental disabilities, and all interested participants were contacted and screened (n=84). Twenty participants met all inclusion criteria and could be scheduled during the study period. A telephone screening was completed with a caregiver of each potential participant to gather demographic information, disability status, history of aggression and self-injurious behaviors, and specific details about the repetitive behaviors. Caregivers were asked to assess the frequency of different types of repetitive behaviors grouped as follows: whole body (e.g., rocking, swaying), head (e.g., rolling, nodding, turning), hand/finger (e.g., flapping/shaking, clapping), locomotion (e.g., twirling, jumping, bouncing), object usage (e.g., spinning/twirling objects, twiddling), or sensory (e.g., covering eyes or ears, rubbing surfaces). Inclusion required at least one of the first four types to occur at least many times per day so enrolled subjects were likely to exhibit the behavior during the session. Object and sensory behaviors were not the target of this study so individuals were excluded if their repetitive behaviors were of this nature only. In addition to exclusions based on insufficient frequency, individuals were excluded from participation in this study if their caregiver reported significant aggression or self-injurious behaviors. Individuals who were over the age of 18 years who served as their own legal guardian were also excluded from the study. Caregivers were given a brief overview of the study and asked the likelihood that the participant would be able to wear the sensors. No exclusions were made on this basis as all caregivers thought the sensors would be tolerated. Caregivers were provided a visual support through a PowerPoint slide deck to provide accessible information about expectations for participation and were encouraged to review the material with the participant prior to the appointment. Mean age of enrolled subjects was 18 years (SD = 4.08; range = 12–31) and all subjects were male.

Behavior Protocol

Sessions were approximately 60 minutes in length and were video recorded. Exposures were selected based on information provided by caregivers during their eligibility phone screening regarding what types of stimuli were likely to evoke a range of repetitive behaviors in their children. These exposures included watching videos, looking at magazines, being left alone, listening to music, engaging in cognitive tasks (Stroop task), engaging in social tasks (telling a story from pictures), and playing with preferred toys.

At the beginning of the visit, both the participant and their caregiver were told about the purpose of the study and permission and assent were obtained. The sensors were then placed on the participant and the participant was left alone (with observers behind a two-way mirror). After approximately 10 minutes, the participant was joined by a researcher who provided the pre-chosen set of activities. We note that the activities often involved hand and body motions (such as interacting with a ball or bubbles), and the participants were not required to be sedentary during the session and often moved around the room. Information on calming tactics was also provided by the caregivers to be used if any participant became agitated. Only one participant became agitated during their visit, resulting in early termination of the session.

Sensor Data Collection

Four sensors were attached to the wrists and torso in locations shown in Figure 1A. Sensors were oriented so that the sensor axes consistently aligned with defined body axes across all subjects. A Zephyr Biopatch (Figure 1B) with electrocardiogram (ECG) sensor and 3-axis accelerometer was placed on the chest using disposable ECG electrodes. The ECG data was not used for this study. Axivity AX3 accelerometers (Figure 1C) were placed on each wrist using a custom wrist band secured with Velcro. An elastic sport wrist band was used to cover the entire band to deter participants from unlatching the Velcro. A third Axivity sensor was attached to the back of the shirt collar with a fitness tracker clip (Withings) to determine if this location was suitable for rocking detection for subjects that needed an “out of sight” option. All sensor data was logged for offline analysis.

Video Coding

The recorded videos were annotated for repetitive behaviors by a trained coder to serve as the ground truth for the automated detection algorithm. The coders were trained and required to demonstrate 85% agreement with the trainer before beginning coding for the study. Video based behavior coding was done using ELAN Linguistic Annotation Software (v 4.9.1)(Wittenburg et al. 2006). Time synched annotation described duration, chief body region (hand/arm, trunk, head/neck), and type of behavior. Types of behavior included flapping, body rocking, pacing, other abnormal repetitive behavior, or functional/non-abnormal repetitive behavior (such as that seen with coloring). A minimum of 20% of annotations for each subject were reviewed by the lead investigators with clinical expertise with developmental disabilities. Concerns, questions, or disagreements about annotation categorization were resolved through review and consensus via the lead investigators. Additionally, all events for which the automated algorithm and the video annotation differed were reviewed by the lead clinical investigator.

For body rocking, both side-to-side (lateral) and front-to-back (sagittal) rocking were included. Rocking could occur while sitting or standing, but rocking while walking was considered abnormal walking and not coded as body rocking. Because single rocks are often indistinguishable from position adjustment, rocking required the torso position to come to the extreme forward or extreme lateral position twice. Repetitive hand movements were coded as hand flapping or “other repetitive” if they were not traditional flapping, but were a repetitive hand motion without an obvious purpose. Repetitive movements with a purpose (e.g. bubble popping, striking a keyboard) were coded as “functional.”

Rocking Detection Algorithm—A rocking detection algorithm was developed in Matlab (Mathworks) using the accelerometer signal from the Zephyr sensor on the chest and later applied to the sensor on the shirt collar. Data from the Zephyr accelerometer was acquired using a sampling rate of 100Hz, and the range is fixed at $\pm 16g$. All three axes were used in the algorithm.

The first step in the rocking detection algorithm was to detect and remove from consideration sections of data where the sensor had fallen off the subject or the subject was pressing on the sensor. These events were detected by baseline signals (0–0.2 Hz) in one or more axis that were outside of the normal range for a properly mounted sensor. Once the “bad data” condition was met, the next 2s of data were also marked as bad. The second step in the algorithm was to detect and remove sections of data corresponding to walking because walking involves a torso movement similar to stereotypical body rocking. Walking was discriminated from body rocking and other repetitive movements by high frequency movement in the vertical axis associated with footfalls and large movement in the lateral axis associated with shifting weight from side-to-side while walking.

The rocking detection was implemented based on the identification of zero crossings with appropriate spacing and regularity to suggest rocking behavior. The lateral and sagittal axes were used to account for both side-to-side and front-to-back rocking, respectively. Both axes were filtered to a band of 0.2–5 Hz, and all zero crossings were located. Any zero-crossings that occurred during times marked as “walking” or “bad data” were eliminated. Then, zero-crossings were eliminated in each axis based on the time between crossings, the height of the peak spanned by the zero-crossings, and the regularity of spacing as detailed in Table 1. After eliminating zero crossings that did not meet these conditions, stereotypy was marked by requiring a minimum number of zero crossings in a row (Figure 2).

Rocking events were marked by combining all events marked as either lateral rocking or sagittal rocking. Additionally, any events separated by less than 5s were combined into one event. Similarly, rocking events in the annotated data were combined if they were separated by less than 5s.

The rocking detection algorithm was then implemented with the accelerometer signal from the Axivity sensor on the shirt collar. Data from this sensor was acquired at 100Hz, and the range was set to $\pm 4g$. The lateral peak threshold was increased when running the algorithm using the data from the sensor on the shirt collar to account for head movements. All other algorithm criteria were unchanged from the chest sensor settings.

Hand-Flapping Detection Algorithm

The accelerometer signals from the Axivity sensors on the left and right wrists were used to detect hand-flapping events. Data was acquired at 100Hz, and the range of the accelerometer is $\pm 4g$. All three axes of accelerometer data were filtered to the band of 0.75–5Hz. Because flapping is less symmetric than rocking, the detection algorithm was based on peak locations rather than zero crossings. Both positive and negative peaks were found in the vertical (threshold: 0.2g), lateral (threshold: 0.35g), and sagittal (threshold: $-0.35g$) signals with a minimum spacing of 0.08 s. A subset of these peaks were marked as potential flapping events if there were at least three peaks in a row with spacing of 0.15–0.75s. For each axis, the number of peaks over a 1s window was computed. If there were at least four peaks marked in each axis for any combination of two axes, or if there were at least three peaks marked in all three axes, the segment was marked as hand-flapping (Figure 3).

Hand-flapping events were marked by combining events marked as flapping on either wrist. Events separated by fewer than 3 seconds were combined into one event. This was also extended to the annotated data for both events annotated as hand flapping and events labeled as “other repetitive” that involved the hands.

Evaluation

Each event identified by the algorithm was characterized as a true positive (TP) or false positive (FP) based on whether there was overlap with an event annotated as rocking. The sensitivity was calculated as $TP/(TP+FN)$ and indicates the percentage of actual events detected by the algorithm. The positive predictive value was calculated as $TP/(TP+FP)$ and indicates the likelihood that an event detected by the algorithm is a true event.

Results

Participation

Data was recorded on 20 participants. Five participants were not usable due to video corruption issues. The remaining 15 subjects, of which five participants rocked and four participants flapped, were analyzed for a total of 11 hours of usable video. Collected sensor data from these 15 subjects were input into separate algorithms for detection of body rocking and hand flapping.

Rocking Detection

Five subjects engaged in body rocking during the session. Table 2 provides the performance of the automated detection algorithm using the accelerometer on the chest.

False positives of the algorithm were evaluated on all 15 subjects with usable data, including those in Table 2 and the 10 subjects who did not engage in body rocking. For the sensor on chest, there were 17 false positives over the 11 hours of recording, corresponding to an average false positive rate of 1.5 per hour. The sensitivity was calculated as 80% by using the total number of TP, FP and FN across all five subjects.

The algorithm was also evaluated using the accelerometer attached to the shirt collar as an “out of sight option” (Table 3). The overall sensitivity and positive predictivity was only slightly reduced for the collar sensor. Evaluating false positives for the collar sensor on all 15 subjects resulted in 19 false positives, for a rate of 1.7 per hour.

The percent of time engaged in rocking was calculated for each session using both the annotated events and the events that were automatically detected by the algorithm (Figure 4). The percent engagement calculated by the algorithm when the sensor on the chest was used exhibited close agreement to the annotated results for all subjects who were engaged in rocking at least 5% of the time. When the sensor on the collar was used, the algorithm underestimated the percent engagement for subject 51 because of the failure to identify the full duration of one long rocking event.

Flapping Detection

Four subjects engaged in hand flapping during the recorded session. Table 4 provides the results of the automated flapping detection algorithm for these four subjects. Sensor data from both wrists were analyzed to include events involving only one hand as well as simultaneous motion. There were a large number of false positive events for hand flapping specific behavior, in particular for subject 4 who engaged in other abnormal repetitive movements that met the definition of stereotypy. If the analysis was extended to include any repetitive hand movements that meet the definition of stereotypy, the number of false positives was greatly reduced. Table 5 provides the results of the automated algorithm for detection of any repetitive hand movements that met the definition of stereotypy, including hand flapping and other movements such as fist pumping.

False positives were computed on all 15 subjects with usable data, including 11 subjects who did not engage in hand flapping. Using the extended definition of any repetitive hand movement that is stereotypy, there were 17 false positives, for an average rate of 1.5 false positives per hour. False positives included talking with hands, popping bubbles, and vigorous striking of keys on a computer keyboard.

A comparison of percent engagement was not completed for the hand flapping because the annotated time lacked the precision to provide a useful benchmark due to the short nature of these events. For example, Figure 5 shows the sagittal acceleration from a flapping event with the time annotated as flapping as well as the time detected as flapping by the algorithm. The annotated time overestimates the time of the event. These small discrepancies can lead to large differences in percent engagement when summed across a large number of events.

Discussion

In this promising proof-of-concept study, common stereotypical motor behaviors were detected using unobtrusive, wearable sensors. Participants wore movement sensors on their wrists, shirt collar, and chest. Participants were not given any tolerance training with the sensors prior to the session other than seeing photographs of the sensors in the visual support PowerPoint presentation. We found better acceptance with the sensor on the shirt collar that could not be seen by the participants. The sensor on the chest also contained an ECG sensor

and was larger than the other sensors. Several participants hit or played with the chest sensor during the recording session, and the sensor fell off in a few cases and had to be reattached. Because the ECG data was not used in this study, a smaller accelerometer could be used on the chest which may reduce these issues. The sensors on the wrist were attached using Velcro straps, and participants tended to play with these when left alone. A sports band was put over the Velcro strap, which eliminated this problem. In short we found that commercial sensors can be affixed in an unobtrusive way and were well tolerated by the majority of the subjects for a period of a couple of hours. This finding bodes well for the proposed use of these devices as monitoring tools for research in ecologic settings and future clinical applications.

The accelerometer data streams were analyzed for rocking and hand flapping behavior. Two separate algorithms were used because the movements are detected by sensors affixed on different body parts and occur on different timescales. As compared to previous studies that used machine learning approaches to identify stereotypy, an algorithm was developed that directly used the amplitude and frequency characteristics of the accelerometer signals. Machine learning algorithms can suffer from overfitting and require a significant volume of data. The algorithm developed in this study is generalizable across individuals, although settings can be customized to better capture specific stereotypy patterns.

Automated rocking detection was performed using data from either the sensor on the chest or the shirt collar. A sensitivity of 80% and positive predictivity of 84% were obtained with the chest sensor. While the sensor on the shirt collar was potentially more prone to errors from head movement, its acceptance was higher among the user population and the overall sensitivity and positive predictivity were only minimally reduced to 79% and 82% respectively. When data from the chest sensor was used, the algorithm performed well for all but one participant (subject 9) whose rocking movements were subtle. The false positive rate was 1.5 events per hour which is more than adequate for monitoring subjects who regularly engage in stereotypical motor behaviors. For perspective, the five subjects that rocked in this study averaged over 13 rocking events per hour. When data from the sensor on the shirt collar was used, the overall false positive rate increased only slightly to 1.7 events per hour. The percent engagement was underestimated for one participant (subject 51) because of the failure to detect the entire duration of a single, long rocking event due to asymmetry in the accelerometer waveform. The automated rocking detection algorithm was originally developed using the chest sensor where this type of asymmetry does not occur. Optimization of the algorithm for specific use with the collar sensor can likely improve the performance. Additionally, performance for both the chest and collar sensor could be improved for individual participants using simple customizations such as disabling lateral rocking detection for participants known to only rock front to back.

Automated hand flapping detection was also performed using a single algorithm across participants. The algorithm detected hand flapping events with 93% sensitivity. Participants engaged in a variety of activities involving the hands including bubble popping, writing, and using a keyboard to ensure that the algorithm provided specificity during potentially confounding activities. The algorithm could not distinguish hand flapping from other repetitive stereotypy involving the hands (i.e., hitting hands together) because the amplitude

and frequency characteristics of the signals were very similar. However, if the objective of monitoring is to assess overall motor stereotypy levels, then this distinction is not significant. The false positive rate one 1.5 events per hour was comparable to rocking detection, and considered acceptable for individuals who regularly engage in stereotypy involving the hands.

A limitation of this study is that it was conducted in clinic with purposeful attempts to evoke these behaviors. The algorithms for hand flapping and body rocking must be tested further in a more expanded and generalizable set of real life activities. The focus was limited to automated detection of body rocking and hand flapping and there were only a small number of subjects who exhibited these behaviors. However, there was large variation across the subjects in the specific stereotypy characteristics and we did not exclude data because of the nature of the rocking or flapping. Rocking while walking was not considered as body rocking but an abnormal type of walking. With further effort, outside the scope of this proof-concept study, this walking stereotype may also be suited for automated detection. Future studies will be aimed at evaluating the approach with a larger number of participants during an expanded set of activities as well as demonstrating use in the home setting.

Because the use of wearable sensors is pervasive, with consumers wearing accelerometers for physical activity tracking, the stigma with tracking is unlikely to be a significant issue. The burden on the individual can be minimized with subjects wearing only one or two sensors, on the dominant flapping wrist or on the torso, depending on whether one or both motor stereotypies are being tracked. While the automated detection results presented here were generated by post-processing logged accelerometer data, the sensors are available in versions with wireless streaming. The algorithm could be implemented on data streamed to a tablet or microprocessor-based system to enable continuous monitoring outside of a clinical setting.

Research and clinical outcome measures are a recognized area of need in ASD and an area of active research (Scahill et al. 2015). Further, translational research has produced promising biomedical and behavioral interventions that have the potential to alter core features of a neuro-developmental disorder (Gross et al. 2015; Homberg et al. 2016). Repetitive behavior is one such core feature which is most commonly associated with ASD, but also seen in many other neuro-developmental disorders. Evaluation of these interventions will depend on improved outcome measurement. This proposed solution for automatic identification of motor stereotypy has several benefits, including 1) ease of implementation in real-world settings; 2) enabling studies addressing open questions related to the biological, sensory, behavioral interpretations of the functions served by RSM behaviors; and 3) enabling researchers and clinicians to quantitatively and efficiently track these movements to assess treatment efficacy. These are key for not only identifying appropriate treatments, but also for monitoring change over time and in response to clinical trials.

Acknowledgments

The project described was supported by the National Center for Advancing Translational Sciences (NCATS), National Institutes of Health, through Grant Award Number UL1TR001111 to the NC TraCS Institute, UNC's NIH

Clinical and Translational Science Award (CTSA). The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.

Funding: This study was funded by the National Center for Advancing Translational Sciences (NCATS), National Institutes of Health, through Grant Award Number UL1TR001111 to the NC TraCS Institute, UNC's NIH Clinical and Translational Science Award (CTSA).

Ethical approval: "All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards."

References

- Albinali F, Goodwin MS, Intille S. Detecting stereotypical motor movements in the classroom using accelerometry and pattern recognition algorithms. *Pervasive and Mobile Computing*. 2012; 8(1): 103–114.
- Aman MG, Singh NN, Stewart AW, Field CJ. The aberrant behavior checklist: a behavior rating scale for the assessment of treatment effects. *Am J Ment Defic*. 1985; 89(5):485–491. [PubMed: 3993694]
- Berry-Kravis E, Hessel D, Abbeduto L, Reiss AL, Beckel-Mitchener A, Urv TK, et al. Outcome measures for clinical trials in fragile X syndrome. *J Dev Behav Pediatr*. 2013; 34(7):508–522. DOI: 10.1097/DBP.0b013e31829d1f20 [PubMed: 24042082]
- Bishop SL, Richler J, Cain AC, Lord C, Floyd F. Predictors of perceived negative impact in mothers of children with autism spectrum disorder. *American Journal on Mental Retardation*. 2007; 112(6): 450–461. [PubMed: 17963436]
- Bishop SL, Richler J, Lord C. Association between restricted and repetitive behaviors and nonverbal IQ in children with autism spectrum disorders. *Child neuropsychology*. 2006; 12(4–5):247–267. [PubMed: 16911971]
- Bodfish JW, Symons FJ, Parker DE, Lewis MH. Varieties of repetitive behavior in autism: comparisons to mental retardation. *J Autism Dev Disord*. 2000; 30(3):237–243. [PubMed: 11055459]
- Boyd BA, Baranek GT, Sideris J, Poe MD, Watson LR, Patten E, et al. Sensory features and repetitive behaviors in children with autism and developmental delays. *Autism Research*. 2010; 3(2):78–87. [PubMed: 20437603]
- Boyd BA, McDonough SG, Bodfish JW. Evidence-based behavioral interventions for repetitive behaviors in autism. *J Autism Dev Disord*. 2012; 42(6):1236–1248. [PubMed: 21584849]
- Carrasco M, Volkmar FR, Bloch MH. Pharmacologic treatment of repetitive behaviors in autism spectrum disorders: evidence of publication bias. *Pediatrics*. 2012; 129(5):e1301–e1310. [PubMed: 22529279]
- Devine SL, Rapp JT, Testa JR, Henrickson ML, Schnerch G. Detecting changes in simulated events using partial-interval recording and momentary time sampling III: Evaluating sensitivity as a function of session length. *Behavioral Interventions*. 2011; 26(2):103–124.
- Eilam D, Zor R, Szechtman H, Hermesh H. Rituals, stereotypy and compulsive behavior in animals and humans. *Neuroscience & Biobehavioral Reviews*. 2006; 30(4):456–471. [PubMed: 16253329]
- Goodwin MS, Intille SS, Albinali F, Velicer WF. Automated detection of stereotypical motor movements. *J Autism Dev Disord*. 2011; 41(6):770–782. DOI: 10.1007/s10803-010-1102-z [PubMed: 20839042]
- Gross C, Hoffmann A, Bassell GJ, Berry-Kravis EM. Therapeutic strategies in fragile X syndrome: from bench to bedside and back. *Neurotherapeutics*. 2015; 12(3):584–608. [PubMed: 25986746]
- Harrop C, McConachie H, Emsley R, Leadbitter K, Green J, Consortium, P. Restricted and repetitive behaviors in autism spectrum disorders and typical development: Cross-sectional and longitudinal comparisons. *J Autism Dev Disord*. 2014; 44(5):1207–1219. [PubMed: 24234675]
- Hoch J, Spofford L, Dimian A, Tervo R, MacLean WE, Symons FJ. A direct comparison of self-injurious and stereotyped motor behavior between preschool-aged children with and without developmental delays. *Journal of pediatric psychology*. 2016; 41(5):566–572. [PubMed: 26514642]

- Homberg JR, Kyzar EJ, Scattoni ML, Norton WH, Pittman J, Gaikwad S, et al. Genetic and environmental modulation of neurodevelopmental disorders: Translational insights from labs to beds. *Brain research bulletin*. 2016; 125:79–91. [PubMed: 27113433]
- Kolt LD, Rapp JT. Assessment of therapists' preferences for discontinuous measurement systems. *Behavioral Interventions*. 2014; 29(4):304–314.
- Lewis MH. Environmental complexity and central nervous system development and function. *Mental retardation and developmental disabilities research reviews*. 2004; 10(2):91–95. [PubMed: 15362162]
- Loftin RL, Odom SL, Lantz JF. Social interaction and repetitive motor behaviors. *J Autism Dev Disord*. 2008; 38(6):1124–1135. [PubMed: 18064552]
- Lounds J, Seltzer MM, Greenberg JS, Shattuck PT, MacLean J, William E. Transition and change in adolescents and young adults with autism: Longitudinal effects on maternal well-being. *American Journal on Mental Retardation*. 2007; 112(6):401–417. [PubMed: 17963433]
- Matson JL, Minshawi NF. Functional assessment of challenging behavior: toward a strategy for applied settings. *Res Dev Disabil*. 2007; 28(4):353–361. DOI: 10.1016/j.ridd.2006.01.005 [PubMed: 16765024]
- Matson JL, Terlonge C, Gonzalez ML, Rivet T. An evaluation of social and adaptive skills in adults with bipolar disorder and severe/profound intellectual disability. *Res Dev Disabil*. 2006; 27(6): 681–687. DOI: 10.1016/j.ridd.2005.10.001 [PubMed: 16343842]
- McCracken JT, Aman MG, McDougle CJ, Tierney E, Shiraga S, Whelan F, et al. Possible influence of variant of the P-glycoprotein gene (MDR1/ABCB1) on clinical response to guanfacine in children with pervasive developmental disorders and hyperactivity. *J Child Adolesc Psychopharmacol*. 2010; 20(1):1–5. DOI: 10.1089/cap.2009.0059 [PubMed: 20166790]
- Nadig A, Lee I, Singh L, Bosshart K, Ozonoff S. How does the topic of conversation affect verbal exchange and eye gaze? A comparison between typical development and high-functioning autism. *Neuropsychologia*. 2010; 48(9):2730–2739. [PubMed: 20493890]
- Oliver C, Petty J, Ruddick L, Bacarese-Hamilton M. The association between repetitive, self-injurious and aggressive behavior in children with severe intellectual disability. *J Autism Dev Disord*. 2012; 42(6):910–919. DOI: 10.1007/s10803-011-1320-z [PubMed: 21720724]
- Pierce K, Courchesne E. Evidence for a cerebellar role in reduced exploration and stereotyped behavior in autism. *Biological psychiatry*. 2001; 49(8):655–664. [PubMed: 11313033]
- Plotz, T., Hammerla, NY., Rozga, A., Reavis, A., Call, N., Abowd, GD. Automatic Assessment of Problem Behavior in Individuals with Developmental Disabilities; Paper presented at the UbiComp '12; Pittsburgh, USA. 2012.
- Rapp JT, Vollmer TR. Stereotypy I: A review of behavioral assessment and treatment. *Res Dev Disabil*. 2005; 26(6):527–547. [PubMed: 15885981]
- Rodrigues JL, Gonçalves N, Costa S, Soares F. Stereotyped movement recognition in children with ASD. *Sensors and Actuators A: Physical*. 2013; 202:162–169.
- Scahill L, Aman MG, Lecavalier L, Halladay AK, Bishop SL, Bodfish JW, et al. Measuring repetitive behaviors as a treatment endpoint in youth with autism spectrum disorder. *Autism*. 2015; 19(1): 38–52. [PubMed: 24259748]
- Shattuck PT, Seltzer MM, Greenberg JS, Orsmond GI, Bolt D, Kring S, et al. Change in autism symptoms and maladaptive behaviors in adolescents and adults with an autism spectrum disorder. *J Autism Dev Disord*. 2007; 37(9):1735–1747. [PubMed: 17146700]
- Wirth O, Slaven J, Taylor MA. Interval sampling methods and measurement error: A computer simulation. *Journal of applied behavior analysis*. 2014; 47(1):83–100. [PubMed: 24127380]
- Wittenburg P, Brugman H, Russel A, Klassmann A, Sloetjes H. Elan: a professional framework for multimodality research. *Proceedings of LREC*. 2006; 2006:5.

Figure 1.
A. Diagram of sensor placement. B. Zephyr Biopatch ECG sensor with 3-axis accelerometer that was placed on the chest. C. Axivity AX3 3-axis accelerometer that was placed on the wrists and shirt collar.

Figure 2.
Example of rocking detection based on zero crossings for acceleration in the sagittal axis.

Figure 3.
Example of flapping detection based on peak locations for acceleration in the sagittal axis.

Figure 4. Comparison of percent engagement in body rocking calculated from the annotation and the automated algorithm.

Figure 5.

Acceleration signal of a flapping event with both the annotated time (solid red) and the algorithm detection time (dashed green) indicated. The annotated time overestimates the length of the event due to lack of precision in the video coding procedure.

Table 1

Criteria of zero-crossings for algorithmic determination of rocking.

	Lateral Axis	Sagittal Axis
Time between crossings	0.75-2s	0.4-2s
Peak height	0.03–0.15g	> 0.075g
Agreement with previous spacing	65–135%	65–135%
Number of crossings	6	4

Table 2

Performance of automated rocking detection algorithm using chest sensor.

Subject ID	True Positives	False Positives	False Negatives	Sensitivity (%)	Positive Predictivity (%)
4	18	3	2	90.0	85.7
9	5	3	6	45.5	62.5
43	2	1	0	100.0	66.7
45	7	1	2	77.8	87.5
51	16	1	2	88.9	94.1
Total	48	9	12	80.0	84.2

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

Table 3

Performance of automated rocking detection algorithm using sensor on back of collar.

Subject ID	True Positives	False Positives	False Negatives	Sensitivity (%)	Positive Predictivity (%)
4	17	5	3	85.0	77.3
9	9	4	3	75.0	69.2
43	0	1	2	0	0
45	8	0	2	80.0	100.0
51	17	1	4	81.0	94.4
Total	51	11	14	78.5	82.3

Table 4

Performance of hand flapping algorithm against behaviors coded as flapping.

Subject ID	True Positives	False Positives	False Negatives	Sensitivity (%)	Positive Predictivity (%)
4	1	34	0	100.0	2.9
45	35	4	7	83.3	89.7
48	3	12	0	100.0	20.0
50	57	28	0	100.0	67.1
Total	96	78	7	93.2	55.2

Author Manuscript

Author Manuscript

Author Manuscript

Author Manuscript

Table 5

Performance of hand flapping algorithm against any repetitive stereotypical behavior involving the hands.

Subject ID	True Positives	False Positives	False Negatives	Sensitivity (%)	Positive Predictivity (%)
4	31	4	2	93.9	88.6
45	38	1	6	86.4	97.4
48	12	3	3	80.0	80.0
50	84	1	5	94.4	98.8
Total	165	9	16	91.2	94.8