J Autism Dev Disord (2011) 41:770–782
DOI 10.1007/s10803-010-1102-z

ORIGINAL PAPER

Automated Detection of Stereotypical Motor Movements

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Published online: 14 September 2010

Abstract To overcome problems with traditional methods for measuring stereotypical motor movements in persons with Autism Spectrum Disorders (ASD), we evaluated the use of wireless three-axis accelerometers and pattern recognition algorithms to automatically detect body rocking and hand flapping in children with ASD. Findings revealed that, on average, pattern recognition algorithms correctly identified approximately 90% of stereotypical motor movements repeatedly observed in both laboratory and classroom settings. Precise and efficient recording of stereotypical motor movements could enable researchers and clinicians to systematically study what functional relations exist between these behaviors and specific antecedents and consequences. These measures could also facilitate efficacy studies of behavioral and pharmacologic interventions intended to replace or decrease the incidence or severity of stereotypical motor movements.

Keywords Stereotypical motor movement · Accelerometry · Pattern recognition

Autism Speaks and the Nancy Lurie Marks Family Foundation funded this research. The sensors were developed through NSF grant #0312065. Special thanks also to Meghan Scrimgeour for help with data collection, coding, and analysis.

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Stereotyped behaviors are generally defined as repetitive interests and/or motor or vocal sequences that appear to an observer to be invariant in form and without any obvious eliciting stimulus or adaptive function (Baumeister and Forehand 1973; Berkson and Davenport 1962; Lewis and Baumeister 1982; Ridley and Baker 1982). According to the DSM-IV-TR (APA 2000), this core feature of Autism Spectrum Disorder (ASD) is identified when a person exhibits at least one of the following: "(a) encompassing preoccupation with one or more stereotyped and restricted patterns of interest that is abnormal either in intensity or focus; (b) apparently inflexible adherence to specific, nonfunctional routines or rituals; (c) stereotyped and repetitive motor mannerisms (e.g., hand or finger flapping or twisting or complex whole-body movements); or (d) persistent preoccupation with parts of objects" (p. 75).

The current work focuses on the stereotyped and repetitive motor mannerisms described in the DSM-IV-TR definition of stereotypy.[1] Several stereotypical motor movements have been identified (Goldman et al. 2009; Lewis and Bodfish 1998; Repp et al. 1992), the most prevalent among them being body rocking, mouthing, and complex hand and finger movements (Goldman et al. 2009; LaGrow and Repp 1984; Symons et al. 2005). Stereotypical motor movements occur frequently in people with mental retardation, developmental disabilities, and genetic syndromes (Bishop et al. 2006; Bodfish et al. 2000; Campbell et al. 1990; Lewis and Bodfish 1998; Militerni et al. 2002; Moss et al. 2009), and less frequently in typically developing children and adults (Rojahn et al. 2000).

[1] The term *stereotypical motor movements* will be used for the remainder of this work to distinguish this class of behavior from all other stereotyped behaviors.

Investigations of ASD have increased in recent years in response to growing awareness of the high prevalence rates, currently estimated to be 1 in 110 (Centers for Disease Control and Prevention 2009). However, the majority of this work focuses on social and communication deficits, rather than on restricted and repetitive behavior (Lewis and Bodfish 1998; Rutter 1996). This is a potential problem given the high prevalence of stereotypical motor movements reported in individuals with ASD. For instance, Berkson and Davenport (1962) found that over two-thirds of individuals with ASD living in an institution engaged in stereotypical motor movements. Campbell and colleagues (1990) and Bodfish et al. (2000) report that 100% of the participants in their studies, totaling 256 persons with ASD, exhibited at least one stereotypical motor movement. Crosland and colleagues (2001) found that 161 out of 165 (97.6%) children with ASD displayed some form of stereotypical motor movement. More recently, Goldman and colleagues (2009) found that between 60–70% of 129 children with ASD engaged in stereotypical motor movements.

When severe, stereotypical motor movements can present several problems for individuals with ASD and their families. First, persons with ASD often engage in stereotypical motor movements. Preventing or stopping these movements can be problematic as individuals with ASD may become anxious, agitated, or aggressive if they are interrupted (Gordon 2000). Second, if unregulated, stereotypical motor movements can become the dominant behavior in an individual with ASD's repertoire and interfere with the acquisition of new skills and performance of established skills (e.g., Koegel and Covert 1972; Koegel et al. 1974; Lovaas et al. 1971; Varni et al. 1979). Third, engagement in these movements is socially inappropriate and stigmatizing and can complicate social integration in school and community settings (Jones et al. 1990; Watkins and Konarski 1987). Finally, stereotypical motor movements are thought to lead to self-injurious behavior under certain environmental conditions (Kennedy 2002).

Hypothesized Functions of Stereotypical Motor Movements

Stereotypical motor movements are complex and thought to serve a multiplicity of functions (Mason 1991; Turner 1999). While no one theory has obtained overwhelming support, there is evidence for biological, behavioral, homeostatic, and sensory interpretations.

Biological

Neurophysiological theories contend that stereotypical motor movements represent the behavioral output of dysregulated neuronal systems (Cooper and Dourish 1990; Dantzer 1986; Lewis et al. 1981; Rapp and Vollmer 2005; Thelen 1981), including the basal ganglia (Canales and Graybiel 2000, 2008; Lewis et al. 1996b; Ridley 1994) and dopaminergic pathways in the brain (Bodfish et al. 1995; Lewis et al. 1987, 1996a).

Behavioral

Behavior-analytic theories suggest that stereotypical motor movements are maintained by reinforcement properties associated with either automatic reinforcement (Vollmer 1994) or social interactions (Iwata et al. 1982). In the automatic reinforcement paradigm, stereotypical motor movements may be reinforcing because the individual has regulatory control over the production of perceptual stimuli (Lovaas et al. 1987). In the social interaction paradigm, stereotypical motor movements are either positively reinforced by gaining attention from others or access to tangible rewards (Kennedy et al. 2000), or negatively reinforced by reducing or escaping from unwanted activities or social interactions (Durand and Carr 1987; Mace and Belfiore 1990).

Homeostatic

Homeostatic theories assume there is an optimal level of stimulation for an individual (Leuba 1955) and that stereotypical motor movements serve a compensatory function to increase arousal in under-stimulating environments or reduce arousal in over-stimulating environments (Brett and Levine 1979; Hutt 1978; Hutt and Hutt 1965, 1970; Hutt et al. 1965; Kinsbourne 1980; Repp et al. 1992).

Sensory

Sensory theories contend that individuals with ASD engage in stereotypical motor movements to modulate auditory, visual, vestibular, tactile, and proprioceptive stimulation (Baranek et al. 1997, 2005; Berkson and Mason 1964; Chen et al. 2009; Cleland and Clark 1966; Edelson 1984; Gabriels et al. 2008; Lourie 1959). In this paradigm, stereotypical motor movements may either be a response to sensory stimulation or to induce a sensory experience (Liss et al. 2006).

These four theoretical interpretations of stereotypical motor movements may not always be mutually exclusive, and may in some instances be integrated and evolve over time (Guess and Carr 1991). For instance, stereotypical motor movements might originate as a biologically determined rhythmic pattern that acquires functionality over time to become a behavioral, homeostatic, or sensory response to control internal and/or external environmental stimulation and/or situations. In order to determine what function a stereotypical motor movement serves for a given individual, accurate and reliable measures of the movements are needed. Unfortunately, as reviewed in more detail below, there are a host of problems associated with traditional methods for measuring stereotypical motor movements that potentially complicate the collection of reliable and valid data with which to confirm or disconfirm any of these hypothesized functions.

Measuring Stereotypical Motor Movements

Traditional measures of stereotypical motor movements rely primarily on paper-and-pencil rating scales, direct behavioral observation, video-based methods, and kinematic analyses, all of which are potentially limiting.

Paper-and-pencil rating scales typically involve a global impression of the frequency and/or severity of stereotypical motor movements based on general, non-specific observations. Several paper-and-pencil rating scales have been developed that ask an informant to give a global impression of an individual's stereotypical motor movements (Lewis and Bodfish 1998; Rojahn et al. 2000). From a measurement standpoint, informant-rating scales are inherently subjective, can have questionable accuracy, and fail to quantify intra-individual variations in the form, amount, intensity, and duration of stereotypical motor movements over time (Pyles et al. 1997).

Direct behavioral observation involves watching and recording a sequence of stereotypical motor movements in real-time. According to Sprague and Newell (1996), the following factors can make direct observational measures unreliable: (a) reduced accuracy in observing and documenting high-speed motor sequences; (b) difficulty determining when a sequence has started and ended; (c) observer errors attributable to memory and the ability to estimate the amount of stereotypical motor movement over a finite period of time; (d) limitations in the ability to observe concomitantly occurring stereotypical motor movements; and (e) limitations in the ability to note environmental antecedents and record stereotypical motor movements at the same time. The few studies evaluating the accuracy of direct behavioral observation methods reflect these problems. For instance, Schultz and Berkson (1995) only found 33% agreement between observations of stereotypical motor movements and teacher reports. Gardenier et al. (2004) assessed two different recording schedules (e.g., partial-interval recording and momentary time sampling) and found that they grossly over- or underestimated the relative frequency and duration of stereotypical motor movements in children with ASD.

Video-based methods involve video capture of behavior and off-line coding and analysis of stereotypical motor movements. The ability to view videos repeatedly and to slow playback speeds makes video-based methods more accurate and reliable than paper-and-pencil and direct behavioral observation methods. Video-based methods, however, are tedious and time consuming, which makes them impractical for most clinicians to use in applied settings on a regular basis (Matson and Nebel-Schwalm 2007). The necessity to code videos off-line also precludes real-time monitoring.

Kinematic analyses involve quantification of motor movements and the forces required to produce them. A variety of kinematic methods have been used to measure stereotypical motor movements, primarily in persons with mental retardation, including kinematic analyses of videotaped movements (Berkson et al. 2001; Newell et al. 1999; Sprague et al. 1996), postural stability tasks (Bodfish et al. 2001; Ko et al. 1992; Newell and Bodfish 2007; Newell et al. 1993), and accelerometry (MacLean et al. 1984; van Emmerick et al. 1993a, b). While these methods are desirable given their objectivity, precision, and ability to quantify motor control properties (motion amplitude, frequency, variability, periodicity, etc.), they too are potentially limiting. Kinematic analyses of videotapes share the same issues as video-based methods mentioned above. Postural stability tasks require specialized equipment (e.g., force platforms) that is fixed in space. Accelerometry methods are promising given their precision and mobility, hence their inclusion in the current research; however, previous usage of these sensors to quantify stereotypical motor movements have relied solely on *1*-axis accelerometers which fail to capture movement dynamics in three dimensional space. Moreover, the data is traditionally processed and analyzed offline, precluding real-time monitoring.

Taken together, traditional methods of documenting stereotypical motor movements are potentially limited. The aim of the current work is to explore whether three-axis wireless accelerometers combined with pattern recognition algorithms can provide an automated measure of stereotypical motor movements that may be more objective, detailed, and precise than rating scales and direct behavioral observation, and more time-efficient and mobile than video-based methods and kinematic analyses.

Accelerometry

Accelerometry offers a practical and low cost method of objectively monitoring human movements, and has particular applicability to the monitoring of free-living participants (Mathie et al. 2004). An accelerometer is an electromechanical sensor that measures acceleration forces. These forces may be static, like the constant force of gravity, or dynamic—caused by moving or vibrating the accelerometer. By measuring the amount of static acceleration due to gravity, one can determine the angle a sensor is titled at. By measuring the amount of dynamic acceleration, one can analyze the way a sensor is moving.

An active area of research with accelerometers is the measurement of physical activity (Welk 2002). The use of multiple sensors permits an algorithm to use the information about relationships between characteristics of movement between different sensors and axes within sensors. Features of each raw signal are computed such as the frequency of motion, the temporal extent and variability of the movement, and the amplitude of motion changes, and then compared between sensors located on different limbs. This is fundamentally different than the approach typically used when researchers deploy actigraphs, which disregard most of this information when they compute a single measure summarizing overall activity levels for a 1–60 s epoch.

Analysis of raw acceleration data also allows detection of specific activities. For example, using a single three-axis accelerometer it is possible to detect the orientation of a sensor (Weinberg and Lemaire 1998). If the sensor is worn at a known orientation on the body, the change of orientation of a limb can be determined (Crossan and Murray-Smith 2004). By comparing the change in orientation of sensors on multiple limbs, relative patterns of motion between limbs can be identified in the signal for some types of distinctive behaviors (Bao and Intille 2004).

Automated Physical Activity Recognition

Recent work has shown that supervised and unsupervised learning pattern classification algorithms can be used to detect a variety of physical activities using acceleration data (Bao and Intille 2004; Kern and Schiele 2003; Wyatt et al. 2005). The most accurate accelerometer-driven activity recognition algorithms reported in past work use nearest neighbor classification with feature vectors computed from raw accelerometer signals. Vectors that encode features such as inter-peak intervals and average AC (alternating current) and DC (direct current) components are compared to vectors representative of the activity, which are either hand-coded or computed from a training set. One such algorithm developed using four, one-axial sensors placed on the sternum, wrist, thigh, and lower leg discriminated between walking, walking down stairs, sitting, and sitting and talking (Foerster et al. 1999). Another nearest neighbor approach achieved recognition rates above 80% for the activities of lying, standing, sitting, walking, and cycling (Bussmann et al. 2001; van den Berg-Emons et al. 2000).

Applying Accelerometers and Pattern Recognition Algorithms to Detect Stereotypical Motor Movements

Given that pattern recognition algorithms can reliably and accurately detect a range of physical activities in the general population using acceleration data and that stereotypical motor movements, by definition, consist of very distinct motion patterns that occur repeatedly, the current work attempts to apply this methodology to the automated detection of stereotypical motor movements in persons with ASD.

To our knowledge, there has only been one published study using accelerometers and pattern recognition algorithms to automatically detect stereotypical motor movements (Westeyn et al 2005). While 69% of hand flapping events were automatically and accurately detected in this work using Hidden Markov Models, the data were acquired from neurotypical individuals mimicking the behaviors—it did not observe children with ASD *actually* performing the behaviors. Therefore, no algorithms have yet been shown to automatically and accurately detect stereotypical motor movements in persons with ASD. In the current work, we sought to develop algorithms for automatically detecting body rocking and hand flapping that advance the state-of-the-art in stereotypical motor movement monitoring in children with ASD. The training and recognition of these behaviors were undertaken in both a laboratory and classroom setting to determine the accuracy of recognition performance using acceleration data obtained in both simulated and real-world environments.

Methods

Participants

Six participants with institutional review board and caregiver consent were recruited from the Groden Center, Inc. The Groden Center is a non-profit educational and treatment school for children and adolescents with ASD and other developmental disabilities located in Providence, Rhode Island. Participants were included in the study if they met the following inclusion criteria: (a) Had a documented DSM-IV-TR diagnosis of ASD made by a licensed psychologist familiar with the child; (b) Were between the ages of 12–20 years; (c) Had a clinically significant score (i.e., "behavior occurs and is a severe problem") on the Whole Body and/or Hand/Finger items included in the Stereotyped Behavior Subscale of the Repetitive Behavior

Table 1 Participant characteristics

Participant	Age (years)	Sex	Diagnosis	CARS	Stereotypy
JK	14	Male	ASD	42	Rocking, Flapping
EH	14	Male	ASD	33	Flapping
CF	13	Male	ASD	43.5	Rocking, Flapping
TM	16	Male	ASD	39	Rocking, Flapping
CS	20	Male	ASD	36	Rocking, Flapping
DB	13	Male	ASD	38	Rocking

CARS childhood autism rating scale, total score

Scale-Revised (RBS-R; Bodfish et al. 2000); (d) Tolerated the accelerometry sensors; and (e) Exhibited, on average, at least 10 hand flapping or body rocking incidents per hour. Participant characteristics are listed in Table 1. All participants were male and ranged in age from 13–20 years. The Childhood Autism Rating Scale (CARS; Schopler et al. 1986) was administered to each participant by a licensed psychologist familiar with the child. Scores on the CARS ranged from 33–43.5 ($M = 38.6$), placing the sample in the moderately to severely autistic range.

Sensors

Each participant wore three wireless accelerometers (Munguia-Tapia et al. 2004) (see Fig. 1) placed simultaneously on the left wrist and right wrist using wristbands, and on the torso using a thin strip of comfortable fabric tied around the chest (see Fig. 2a, b). The wrists and torso were chosen because stereotypical hand flapping and body rocking are associated with movements in these areas. The sensors were small enough to be worn on these locations comfortably and without restricting movement. All participants tolerated wearing the sensors for the duration of each observation. Visual inspection of each participant's real-time acceleration data prior to analysis confirmed that there were no equipment failures or other problems occurring (improper attachment, weak signal strength, unusual amount of signal loss, etc.). The devices were set to transmit 3-axis ± 2 g motion data at 60 Hz to a nearby receiver (see Fig. 2c). The receiver was plugged into a standard computer (desktop in the laboratory and laptop in the classroom), where data from the three sensors were

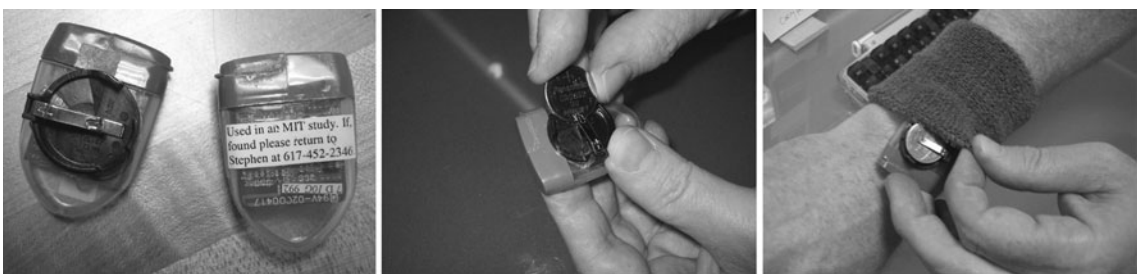

Fig. 1 The MITes 3-axis wireless accelerometer sensors housed in plastic cases with external battery holder. The cases can be worn on the wrists using elastic armbands

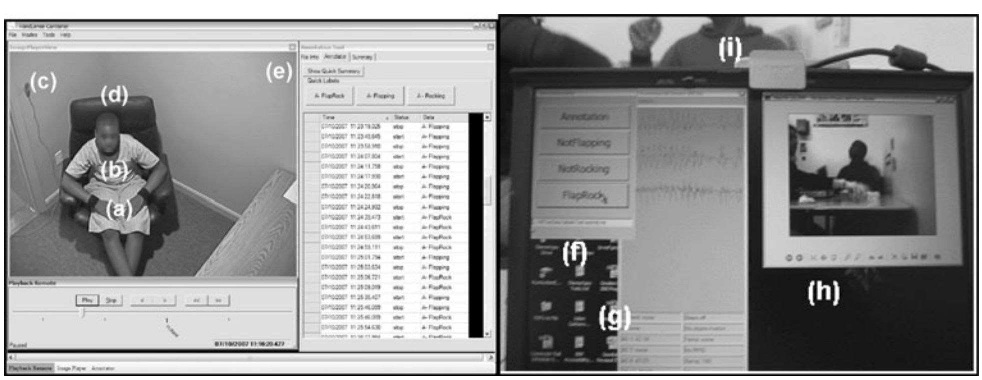

Fig. 2 **a** A wireless accelerometer placed on each wrist. **b** A wireless accelerometer placed on the torso. **c** Receiver for sensor data. **d** An image of a child in the laboratory setting. **e** The video coding software that allows frame-accurate annotation. **f** The real-time activity annotator. **g** The acceleration data window plotting data streams in real-time. **h** The video window with images being captured. **i** USB camera clipped on to the top of the laptop

synchronized and saved to disk. Simultaneously, a video camera was used to capture video of the scene that could be synchronized with the accelerometer streams and used for annotation of activity.

Setting

We undertook data collection in both laboratory and classroom settings to determine the accuracy of recognition performance across both constrained and real-world environments. Participants were seated during all observations in both environments.

Laboratory

In the laboratory setting there were limited stimulus materials, one-to-one monitoring by a familiar teacher, and no other students present. The lab is divided into three areas: (1) A soundproof room equipped with a discrete, ceiling mounted camera and microphone to record observations; (2) An observation area behind the glass; and (3) An adjacent office containing a computer and video monitor. While wearing the sensors, participants were observed repeatedly in the lab while sitting in a comfortable chair with a familiar teacher (see Fig. 2d). There were no structured activities involved in these observational sessions. However, teachers familiar with the participants were invited to bring objects (e.g., headphones, books, toys) that participants typically interacted with when engaging in stereotypical motor movements.

Classroom

The classroom setting included a diverse set of stimuli, demands for shared attention, and other students present. Observations included typical classroom activities (e.g., eating lunch, spelling program, sorting), with participants working both on their own and with a familiar teacher.

Observer Coded Stereotypical Motor Movements

Video Coding

A digital camera (mounted in the ceiling of the laboratory; attached to the front of the laptop in the classroom (see Fig. 2i) was used to record each session. The camera was connected to a computer that synchronized the saved video with the accelerometer data streams. Start time, end time, and type of stereotypical motor movement were coded offline by two independent raters using custom video coding software (see Fig. 1e).

Real-Time Coding

Start time, end time, and type of stereotypical motor movement were also coded in real-time using custom annotation software (see Fig. 2f). The activity annotator included three buttons that corresponded to the stereotypical motor movements under observation (i.e., hand flapping, body rocking, and simultaneous hand flapping and body rocking, which we dubbed "flaprock"). Pressing a button once marked the start of the corresponding stereotypical motor movement. Pressing a button a second time marked the end of the corresponding stereotypical motor movement.

Results

Data Collection

Over a period of 12 months, during regular school hours, we recorded one 15–30 min session per week per participant. This data collection effort resulted in a total of 6.5 h of data obtained in the laboratory and 4.75 h of data in the classroom. Observations included at least two sessions per participant per setting.

Participant Stereotypical Motor Movements

Table 2 summarizes stereotypical motor movement characteristics of the participants based on the video records obtained across observation sessions in the laboratory and classroom. *Total Duration* is the total time spent engaged in stereotypical motor movements across all observational sessions. *Percent Engaged* is the percentage of time participants engaged in stereotypical motor movements across all observational sessions. *M* and SD are the mean and standard deviation duration of each participant's stereotypical motor movements, respectively. *Num Stereo* is the number of different types of stereotypical motor movements observed and *Total Stereo* is the cumulative frequency of those movements across observational sessions. Frequency was calculated as the number of each topographical stereotypical motor movement start and end time epoch.

Reliability of Video and Real-Time Codes

Cohen's kappa (Cohen, 1960) was calculated to assess reliability between: (1) Two independent raters for the video codes, and (2) agreement between the video codes and the real-time activity annotations. Kappa values of 0.01–0.20 indicate slight agreement, 0.41–0.60 indicates

Table 2 Summary of participant stereotypical motor movements

Participant	Total duration [min:sec]	Percentage engaged (%)	M (SD)	Num stereo I total stereo [sec]
JK	47:42	28.0	7 (6)	3 I 372
EH	18:18	17.5	3 (2)	2 I 345
CF	10:00	8.5	4 (2)	3 I 149
TM	36:53	45.0	9 (12)	2 I 240
CS	32:14	48.0	7 (7)	3 I 253
DB	67:28	71.0	21 (23)	2 I 199

Num Stereo is the total number of different types of stereotypical motor movements observed. *Total Stereo* is the cumulative frequency of those movements across sessions

moderate agreement, and 0.81–0.99 indicates almost perfect agreement (Landis and Koch 1977).

Video codes were considered in agreement if both raters labeled the same type of stereotypical motor movement, and if the start time and end time for each label was within a one-second margin of difference. A one-second margin of difference was selected to be conservative criteria for agreement given the importance of establishing accurate "ground truth" codes to calculate stereotypical motor movement frequency and duration, and to compare the performance of the pattern recognition algorithms. Real-time codes were considered in agreement if they matched the same type of stereotypical motor movement labeled in the video codes, and if the start time and end time for each label was within a two-second margin of difference. A two-second margin of difference was selected as a more liberal criterion for agreement given the inherent difficulty in observing and documenting high speed, rapidly fluctuating, and often co-occurring movements in real-time.

Kappa values for video codes (*K-video*) and real-time codes (*K-real*), averaged across each participant's sessions in the laboratory and classroom, are listed in Table 3. Agreement between annotators in the video codes ranged from $k = 0.82$–0.95 ($M = 0.87$) in the laboratory and $k = 0.72$–0.92 ($M = 0.84$) in the classroom. Agreement between video codes and real-time codes ranged from $k = 0.33$–0.81 ($M = 0.56$) in the laboratory and $k = 0.32$–0.76 ($M = 0.57$) in the classroom.

Pattern Recognition

The pattern recognition algorithm used five time and frequency domain features computed for each acceleration stream (see Fig. 3): (a) The distances between the means of the axes to capture sensor orientation; (b) Variance to capture variability in different movement directions; (c) Correlation coefficients to capture simultaneous motion in each axis direction; (d) Entropy to capture the type of stereotypical motor movement; and (e) Fast Fourier Transform (FFT) peaks and frequencies to capture differentiation between intensities of stereotypical motor movements. The features were computed for a window of data, assembled into a vector, and used as input to a C4.5 classifier in the WEKA toolkit (Witten and Frank 1999). WEKA was then used to evaluate classification performance using tenfold cross validation.

Stereotypical motor movements were labeled as flapping, rocking, or flaprock. Motor movements that were not stereotypical were labeled as unknown segments. Including an "unknown" class resulted in highly skewed class distributions, such that the frequencies of stereotypical motor movements were substantially lower than examples of the unknown class. To reduce skewness in the data, all classifiers used balanced data for training and natural imbalanced data for testing. Balancing the data was done by randomly under-sampling the majority class (i.e., unknown) and re-sampling minority classes (i.e., stereotypical motor movements).

Nine acceleration streams (i.e., x, y, and z from the three accelerometers) were broken into 50% overlapping sliding windows of 1-s length. Overlapping windows are commonly used in physical activity recognition because they increase the number of data points used to compute movement features, and thus minimize boundary conditions that arise when partitioning the data into independent sequential windows. Our choice of 1-s windows was based on pilot work where we changed the window length from 200 ms to 5-s and measured the performance of the C4.5 classifier over pilot datasets. A window of 1-s obtained good overall accuracy in our sample while minimizing classification delay. Cubic spline interpolation was used to fill in missing data points (e.g., due to wireless signal loss). Windows that lost more than 50% of their expected data points were excluded from the analysis. This amounted to less than 1% of the data.

Table 3 lists performance results of the algorithm averaged over multiple sessions for each participant in the laboratory and classroom. *Accuracy* is the overall percentage of correctly classified stereotypical motor movements divided by the total number of stereotypical motor movements and non-stereotypical motor movements (i.e., unknown class). TP and FP are true and false positive rates, respectively. TP is the proportion of specific stereotypical motor movements that were correctly classified. FP is the

Table 3 Average laboratory and classroom video coding reliability, real-time coding reliability, and pattern recognition performance

Laboratory						Classroom				
	K-video	K-real	Accuracy (%)	TP	FP	K-video	K-real	Accuracy (%)	TP	FP
JK	0.82	0.55	82.5	0.75	0.08	0.72	0.42	85.9	0.82	0.07
EH	0.85	0.37	92.9	0.86	0.12	0.83	0.32	88.9	0.89	0.12
CF	0.89	0.33	91.0	0.76	0.07	0.86	0.54	90.6	0.74	0.07
TM	0.95	0.69	93.7	0.90	0.05	0.92	0.76	93.7	0.90	0.05
CS	0.86	0.59	90.0	0.87	0.09	0.83	0.71	90.2	0.85	0.08
DB	0.88	0.81	96.4	0.91	0.03	0.88	0.68	93.0	0.90	0.07
MEAN	0.87	0.56	91.1	0.84	0.07	0.84	0.57	90.4	0.85	0.08

K-video is kappa for two independent raters for the video codes. *K-real* is kappa between the video codes and the real-time activity annotations. *Accuracy* is the overall percentage of correctly classified stereotypical motor movements divided by the total number of stereotypical motor movements and non-stereotypical motor movements. *TP* and *FP* are true and false positive rates, respectively

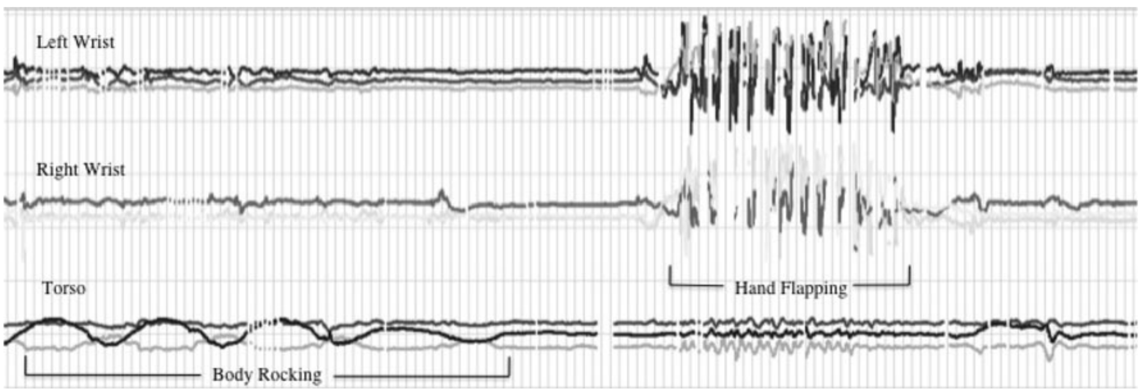

Fig. 3 Acceleration plot showing hand flapping and body rocking stereotypical motor movements for one of the participants with ASD. (*Top*) Left wrist. (*Middle*) Right wrist. (*Bottom*) Torso

proportion of specific stereotypical motor movements that were incorrectly classified. All of these performance measures can be multiplied by 100 and expressed as percentages.[2] Accuracy ranged from 82.5%–96.4% ($M = 91.1\%$) in the laboratory and 85.9%–93.7% ($M = 90.4\%$) in the classroom. TP ranged from 0.75–0.91 ($M = 0.84$) in the laboratory and 0.74–0.90 ($M = 0.85$) in the classroom. FP ranged from 0.03–0.12 ($M = 0.07$) in the laboratory and 0.05–0.12 ($M = 0.08$) in the classroom.

Discussion

As summarized in Table 3, the pattern recognition algorithm, on average, performed very well at automatically detecting stereotypical motor movements across participants in both the laboratory and classroom setting, suggesting that three-axis wireless accelerometers and pattern recognition algorithms are a useful means of monitoring stereotypical body rocking and hand flapping in children with ASD, both in artificial and natural settings.[3] Moreover, inspection of average real-time and video-coded reliabilities in Table 3 confirm that real-time annotation is not a very reliable means for accurately documenting stereotypical motor movements (i.e., $k =$ approximately .60 in both settings), while video annotation can establish highly accurate records of stereotypical motor movements (i.e., $k =$ approximately .85 in both settings). Given the time and resource intensiveness of video annotation methods, and the high accuracy of automated detection demonstrated here, our preliminary results suggest that

[2] See Minnen et al. (2006) and Ward et al. (2006) for a more detailed description of how these performance measures are calculated.

[3] Due to space limitations, only general findings are discussed here. See Albinali et al. (2009) for an extended discussion of these findings at the individual participant level, including how the duration of stereotypical motor movements, the percentage of time engaged in stereotypical motor movements, and the consistency with which a stereotypical motor movement is performed impacts recognition accuracy. Albinali et al. (2009) also reports on additional analyses performed on this dataset, including: (1) Training on laboratory data and testing on classroom data, and vice versa; (2) Training on real-time vs. video records; and (3) Training on data from all participants but one and testing performance on the left out participant.

accelerometers and pattern recognition may provide a measure of stereotypical motor movements that is more objective, detailed, and precise than rating scales and direct behavioral observation, and more time-efficient and mobile than video-based methods and kinematic analyses.

The subjectivity and potential inaccuracy associated with traditional paper-and-pencil and direct observation methods introduce unknown amounts of error into measurement. Measurement error can make baseline rates of an individual's stereotypical motor movements unreliable and thus obfuscate the ability to determine whether a significant change in frequency or duration has occurred over time. The precision of measurement demonstrated in the current work may enable more accurate baseline rates to be obtained. Accurate baseline measures are critical for determining the functional significance of an individual's stereotypical motor movements, and for guiding appropriate intervention efforts.

While we are encouraged by our preliminary results, there are a variety of ways to improve upon and extend the current study. For instance, only six male adolescents with moderate-to-severe ASD participated; future work that includes a more diverse and representative sample is needed in order to generalize our findings to younger children with ASD, females with ASD, and individuals with high functioning autism (HFA). Only questions about perceived frequency of Whole Body and Hand/Finger mannerisms from the RBS-R were administered. Future research that administers the complete RBS-R in conjunction with our automated system could help determine how stereotypical motor movements fit into the larger context of restricted and repetitive behaviors, and to assess what shared and unique information is gathered when using survey measures and our sensor-enabled methodology (i.e., determine exactly what automated methods capture over and above rating scales).

Future work could also assess how the number of sensors and their placement on the body affect recognition results. The current work used three accelerometers placed on the wrists and torso of each participant. Additional sensors could be placed on the body (e.g., upper arm or elbow) to see if more discriminatory features could be obtained for algorithms to match on. Future research could also explore different sliding window lengths and assess their impact on recognition performance. In the present study, 1-s window segmentation was selected because it captured the greatest number of quick and repetitive movements observed in the six participants who contributed data. However, more systematic evaluations of both shorter and longer window lengths could be explored. A potentially useful way to determine optimal window lengths would be to adjust this parameter iteratively in an initial calibration phase and assess which lengths best capture an individual's movement features. If movement-specific windows could be identified, there would likely be significant improvements in feature computation and recognition performance.

Another potential limitation of the current work is that we employed participant-dependent training. Ideally, an algorithm that automatically recognizes stereotypical motor movements would not require training data from a particular individual; instead, it would use a corpus of training data acquired in advance from a large cohort of individuals with ASD who engage in this class of behavior. As more individuals who engage in stereotypical motor movements are observed with accelerometers and pattern recognition algorithms, it would be interesting to see if a pooled data set can be used to classify movements in a person it has not trained on. Finally, while we are encouraged by our pilot results, highly trained behavior and computer scientists carried out the study in relatively short sessions of a few hours each. Future studies are needed to evaluate how well our system performs when used by other researchers, teachers, and caregivers over more extended periods of time. These studies could also help determine the minimum amount of training data that users have to provide recognition algorithms to achieve reasonable performance. Generally speaking, recognition algorithms perform better when they have more training data to learn from. However, providing this data can be time consuming and burdensome. Such user and training set evaluations would ultimately help determine how difficult it would be for end-users to interactively train and test activity recognition algorithms in practice.

If our automated detection results are in fact replicable, a variety of potentially informative analyses could be undertaken using the accelerometer data generated by our system. For instance, time series analysis (Box and Jenkins 1976; Chatfield 1996; Glass et al. 1975; Pena et al. 2001; Velicer and Fava 2003) could determine if there is regularity in intensity and/or variance in how movements are performed within individuals over time. Survival analysis (Kalbfleisch and Prentice 2002; Lawless 2002; Lee and Wang 2003) and point process models (Blossfeld and Rohwer 2002; Diggle 1998; Lindsey 1999) could assess the likelihood of a stereotypical motor movement occurring, test for differences between rates across stereotypical motor movements and/or individuals, and model the influences covariates such as environmental or physiological antecedents and consequences have on movement rates. Pattern-based methods, such as cluster analysis and growth mixture models (Bergman and Magnusson 1997; Dumenci and Windle 2001; Nagin 1999), could be used to classify individuals into more homogenous groups on the basis of similar or dissimilar types and rates of stereotypical motor movements observed. Such analyses could shed light on potential underlying mechanisms and environmental interactions that maintain these behaviors (Hall et al. 2003). Invariant rates of stereotypical motor movements, regardless of environmental setting, would suggest a biological substrate while systematic fluctuations in movement rates across environments or in the presence of certain stimuli would suggest behavioral, homeostatic, or sensory substrates (Repp et al. 1992).

These analyses could also guide and evaluate intervention efforts (Rapp and Vollmer 2005), including making predictions about which treatments would be most effective (Repp et al. 1992). For instance, individuals with ASD who display high levels of stereotypical motor movements across all situations may be suitable candidates for pharmacological intervention (Lewis et al. 1995), whereas individuals who display high levels of stereotypical motor movements only in some situations may be most suitable for behavioral interventions (Dib and Sturmey 2007; Lancioni et al. 2009; Loftin et al. 2008). This line of thinking is underscored by a relatively recent meta-analysis of published treatment literature concluding that interventions are approximately twice as likely to succeed if they target a stereotypical motor movement's underlying function (Carr et al. 1999). Finally, the system developed in this work may prove to be a more efficient, objective, accurate, and sensitive outcome measure than observer-quantified approaches when assessing the effects of behavioral and pharmacological interventions intended to decrease the incidence or severity of stereotypical motor movements.

It is commonly accepted in science and medicine that accurate measurement of observable features or symptoms is a prerequisite to understanding a given phenomenon or condition. While stereotypical motor movements have been observed and clinically documented in persons with ASD since the condition's inception, relatively little work has focused on developing efficient, precise, and detailed measures of this behavior. This delay is likely attributable to the fact that the field has been, and continues to be, so engrossed with clinical problems that the basic property of measurement has been overlooked. It is hoped that the system developed in this work will help redress this imbalance by laying the groundwork for more efficient and precise measurement of stereotypical motor movements, and shed light on one of the most prevalent and least understood behaviors seen in persons with ASD.

References

Albinali, F., Goodwin, M. S., & Intille, S. S. (2009). Recognizing stereotypical motor movements in the laboratory and classroom: A case study with children on the autism spectrum. In *Proceedings of the 11th international conference on ubiquitous computing* (pp. 71–80). New York: ACM Press.

American Psychiatric Association. (2000). *Diagnostic and statistical manual on mental disorders,* (4th ed.). text revision. Washington, DC: Author.

Bao, L., & Intille, S. S. (2004). Activity recognition from user-annotated acceleration data. In A. Ferscha & F. Mattern (Eds.), *Proceedings of PERVASIVE 2004* (Vol. 3001, pp. 1–17). Berlin: Springer.

Baranek, G. T., Foster, L. G., & Berkson, G. (1997). Tactile defensiveness and stereotyped behaviors. *American Journal of Occupational Therapy, 51*, 91–95.

Baranek, G. T., Parham, L. D., & Bodfish, J. W. (2005). Sensory and motor features in autism: Assessment and intervention. In F. Volkmar, R. Paul, A. Klin, & D. Cohen (Eds.), *Handbook of autism and pervasive developmental disorders, 3rd ed., Vol. 2. Assessment, interventions, and policy* (pp. 831–861). New York: Wiley.

Baumeister, A. A., & Forehand, R. (1973). Stereotyped acts. In N. R. Ellis (Ed.), *International review of research in mental retardation* (Vol. 6, pp. 55–96). New York: Academic Press.

Bergman, L. R., & Magnusson, D. (1997). A person-oriented approach in research on developmental psychopathology. *Development and Psychopathology, 9*, 291–319.

Berkson, G., Andriacchi, T., & Sherman, L. (2001). More information on the nature of stereotyped body-rocking. *American Journal on Mental Retardation, 106*, 205–208.

Berkson, G., & Davenport, R. K. (1962). Stereotyped movements of mental defectives. *American Journal of Mental Deficiency, 66*, 849–852.

Berkson, G., & Mason, W. A. (1964). Stereotyped behaviors of chimpanzees: Relation to general arousal and alternative activities. *Perceptual and Motor Skills, 19*, 635–652.

Bishop, S. L., Richler, J., & Lord, C. (2006). Association between restricted and repetitive behaviors and nonverbal IQ in children with autism spectrum disorders. *Child Neuropsychiatry, 12*, 247–267.

Blossfeld, H. P., & Rohwer, G. (2002). *Techniques of event history modeling: New approaches to causal analysis* (2nd ed.). Mahwah, NJ: Lawrence Erlbaum.

Bodfish, J. W., Parker, D. E., Lewis, M. H., Sprague, R. L., & Newell, K. M. (2001). Stereotypy and motor control: Differences in the postural stability dynamics of persons with stereotyped and dyskinetic movement disorders. *American Journal on Mental Retardation, 106*, 123–134.

Bodfish, J. W., Powell, S. B., Golden, R. N., & Lewis, M. H. (1995). Blink rate as an index of dopamine function in adults with mental retardation and repetitive behavior disorders. *American Journal on Mental Retardation, 99*, 344–3355.

Bodfish, J. W., Symons, F. J., Parker, D. E., & Lewis, M. H. (2000). Varieties of repetitive behaviors in autism: Comparisons to mental retardation. *Journal of Autism and Developmental Disorders, 30*, 237–243.

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis, forecasting, and control*. San Francisco: Holden-Day.

Brett, L. P., & Levine, S. (1979). Schedule-induced polydipsia and pituitary-adrenal activity in rats. *Journal of Comparative and Physiological Psychology, 93*, 946–956.

Bussmann, J. B., Martens, W. L., Tulen, J. H., Schasfoort, F. C., van den Berg-Emons, H. J., & Stam, H. J. (2001). Measuring daily behavior using ambulatory accelerometry: The activity monitor. *Behavior Research Methods, Instruments, & Computers, 33*, 349–356.

Campbell, M., Locascio, J. J., Choroco, M. C., Spencer, E. K., Malone, R. P., Kafanteris, V., et al. (1990). Stereotypies and tardive dyskinesia: Abnormal movements in autistic children. *Psychopharmacology Bulletin, 26*, 260–266.

Canales, J. J., & Graybiel, A. M. (2000). A measure of striatal function predicts motor stereotypy. *Nature Neuroscience, 3*, 377–383.

Carr, E. G., Horner, R. H., Turnbull, A. P., Marquis, J. G., Magito-McLaughlin, D., McAtee, M., et al. (1999). *Positive behavior* *support for people with developmental disabilities: A research synthesis*. Washington, DC: American Association on Mental Retardation.

Centers for Disease Control and Prevention (2009). Prevalence of Autism Spectrum Disorders–Autism and Developmental Disabilities Monitoring Network, United States, 2006. Surveillance Summaries, [December 18, 2009]. *MMWR*, 58 (No. SS-10).

Chatfield, C. (1996). *The analysis of time series: An introduction* (6th ed.). Boca Raton, FL: CRC Press.

Chen, Y., Rodgers, J., & McConachie, H. (2009). Restricted and repetitive behaviours, sensory processing and cognitive style in children with autism spectrum disorders. *Journal of Autism and Developmental Disorders, 39*, 635–642.

Cleland, C. C., & Clark, C. M. (1966). Sensory deprivation and aberrant behavior among idiots. *American Journal of Mental Deficiency, 71*, 213–225.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement, 20*, 37–46.

Cooper, S. J., & Dourish, C. T. (1990). *Neurobiology of stereotyped behavior*. New York: Oxford University Press.

Crosland, K. A., Zarcone, J. R., Schroeder, S. R. & Reese, R. M. (2001). Prevalence of stereotypy among children diagnosed with autism at a tertiary referral clinic. Symposium given at the annual meeting of the Association for Behavioral Analysis, New Orleans, LA.

Crossan, A., & Murray-Smith, R. (2004). Variability in wrist-tilt accelerometer-based gesture interfaces. In S. Brewster & M. Dunlop (Eds.), *Proceedings of mobile human-computer interaction—MobileHCI 2004: 6th international symposium* (Vol. 3160, pp. 144–155). Berlin: Springer.

Dantzer, R. (1986). Behavioral, physiological and functional aspects of stereotyped behavior: A review and a reinterpretation. *Journal of Animal Science, 62*, 1776–1786.

Dib, N., & Sturmey, P. (2007). Reducing student stereotypy by improving teachers' implementation of discrete-trial teaching. *Journal of Applied Behavior Analysis, 40*, 339–343.

Diggle, P. J. (1998). An approach to the analysis of repeated measurements. *Biometrics, 44*, 959–971.

Dumenci, L., & Windle, M. (2001). Cluster analysis as a method of recovering types of intraindividual growth trajectories: A Monte Carlo study. *Multivariate Behavioral Research, 36*, 501–522.

Durand, V. M., & Carr, E. G. (1987). Social influences on self-stimulatory behavior: Analysis and treatment application. *Journal of Applied Behavior Analysis, 20*, 119–132.

Edelson, S. M. (1984). Implications of sensory stimulation in self-destructive behaviour. *American Journal of Mental Deficiency, 89*, 140–145.

Foerster, F., Smeja, M., & Fahrenberg, J. (1999). Detection of posture and motion by accelerometry: A validation in ambulatory monitoring. *Computers in Human Behavior, 15*, 571–583.

Gabriels, R. L., Agnew, J. A., Miller, L. J., Gralla, J., Pan, Z., Goldson, E., et al. (2008). Is there a relationship between restricted, repetitive, stereotyped behaviors and interests and abnormal sensory response in children with autism spectrum disorders? *Research in Autism Spectrum Disorders, 2*, 660–670.

Gardenier, N., MacDonald, R., & Green, G. (2004). Comparison of direct observational methods for measuring stereotypic behavior in children with autism spectrum disorders. *Research in Developmental Disabilities, 25*, 99–118.

Glass, G. V., Wilson, V. L., & Gottman, J. M. (1975). *Design and analysis of time series experiments*. Boulder: Colorado Associate University Press.

Goldman, S., Wang, C., Salgado, M. W., Greene, P. E., Kim, M., & Rapin, I. (2009). Motor stereotypies in children with autism and other developmental disorders. *Developmental Medicine and Child Neurology, 51*, 30–38.

Gordon, C. T. (2000). Commentary: Considerations on the pharmacological treatment of compulsions and stereotypies with serotonin reuptake inhibitors in pervasive developmental disorders. *Journal of Autism and Developmental Disorders, 30*, 437–438.

Graybiel, A. M. (2008). Habits, rituals, and the evaluative brain. *The Annual Review of Neuroscience, 31*, 359–387.

Guess, D., & Carr, E. (1991). Emergence and maintenance of stereotypy and self-injury. *American Journal of Mental Retardation, 96*, 299–319.

Hall, S., Thorns, T., & Oliver, C. (2003). Structural and environmental characteristics of stereotyped behaviors. *American Journal on Mental Retardation, 6*, 391–402.

Hutt, C. (1978). Ethology and research in infantile autism. *Bibliotheca Psychiatrica, 157*, 34–44.

Hutt, C., & Hutt, S. J. (1965). Effects of environmental complexity on stereotyped behaviours in children. *Animal Behaviour, 13*, 1–4.

Hutt, C., & Hutt, S. J. (1970). Stereotypies and their relation to arousal: A study of autistic children. In S. J. Hutt & C. J. Hutt (Eds.), *Behavior studies in psychiatry* (pp. 175–204). New York: Pergammon Press.

Hutt, S. J., Hutt, C., Lee, D., & Ounsted, C. (1965). A behavioural and electro-encephalographic study of autistic children. *Journal of Psychiatry, 3*, 181–197.

Iwata, B. A., Dorsey, M., Slifer, K., Bauman, K., & Richman, G. (1982). Toward a functional analysis of self-injury. *Analysis and Intervention in Developmental Disabilities, 2*, 3–20.

Jones, R. S. P., Wint, D., & Ellis, N. C. (1990). The social effects of stereotyped behavior. *Journal of Mental Deficiency Research, 34*, 261–268.

Kalbfleisch, J. D., & Prentice, R. L. (2002). *The statistical analysis of failure time data* (2nd ed.). New York: Wiley.

Kennedy, C. H. (2002). Evolution of stereotypy into self-injury. In S. R. Schroeder, M. L. Oster-Granite, et al. (Eds.), *Self-injurious behavior: Gene-brain behavior relationships* (pp. 133–143). Washington, DC: American Psychological Association.

Kennedy, C. H., Meyer, K. A., Knowles, T., & Shulka, S. (2000). Analyzing the multiple functions of stereotypical behavior for students with autism: Implications for assessment and treatment. *Journal of Applied Behavior Analysis, 33*, 559–571.

Kern, N., & Schiele, B. (2003). Context-aware notification for wearable computing. In *Proceedings of the 7th international symposium on wearable computing* (pp. 223–230). Piscataway: IEEE Press.

Kinsbourne, M. (1980). Do repetitive movement patterns in children and animals serve a de- arousing function? *Developmental and Behavioral Pediatrics, 1*, 39–42.

Ko, Y. G., van Emmerick, R. E. A., Sprague, R. L., & Newell, K. M. (1992). Postural stability, tardive dyskinesia and developmental disability. *Journal of Intellectual Disability, 36*, 309–323.

Koegel, R. L., & Covert, A. (1972). The relationship of self-stimulation to learning in autistic children. *Journal of Applied Behavior Analysis, 5*, 381–387.

Koegel, R. F., Firestone, P. B., Kramme, K. W., & Dunlap, G. (1974). Increasing spontaneous play by suppressing self-stimulation in autistic children. *Journal of Applied Behavior Analysis, 7*, 521–528.

LaGrow, S. J., & Repp, A. C. (1984). Stereotypic responding: A review of intervention research. *American Journal of Mental Deficiency, 88*, 595–609.

Lancioni, G. E., Singh, N. N., O'Reilly, M. F., & Sigafoos, J. (2009). An overview of behavioral strategies for reducing hand-related stereotypies of persons with severe to profound intellectual and multiple disabilities: 1995–2007. *Research in Developmental Disabilities, 30*, 20–43.

Landis, J. R., & Koch, C. G. (1977). The measurement of observer agreement for categorical data. *Biometrics, 33*, 159–174.

Lawless, J. F. (2002). *Statistical models and methods for lifetime data* (2nd ed.). New York: Wiley.

Lee, E. T., & Wang, J. W. (2003). *Statistical methods for survival data analysis* (3rd ed.). New York: Wiley.

Leuba, C. (1955). Toward some integration of learning theories: The concept of optimal stimulation. *Psychological Reports, 1*, 27–33.

Lewis, M. H., & Baumeister, A. A. (1982). Stereotyped mannerisms in mentally retarded persons: Animal models and theoretical analyses. In N. R. Ellis (Ed.), *International review of research in mental retardation* (Vol. 11, pp. 123–161). New York: Academic Press.

Lewis, M. H., Baumeister, A. A., & Mailman, R. B. (1987). A neurobiological alternative to the perceptual reinforcement hypothesis of stereotyped behavior: A commentary on "Self-stimulatory behavior and perceptual reinforcement". *Journal of Applied Behavior Analysis, 20*, 253–258.

Lewis, M. H., & Bodfish, J. W. (1998). Repetitive behavior disorders in autism. *Mental Retardation and Developmental Disabilities Research Reviews, 4*, 80–89.

Lewis, M. H., Bodfish, J. W., Powell, S. B., & Golden, R. N. (1995). Clomipramine treatment for stereotypy and related repetitive movement disorders associated with mental retardation. *American Journal on Mental Retardation, 100*, 299–312.

Lewis, M. H., Bodfish, J. W., Powell, S. B., Wiest, K., Darling, M., & Golden, R. N. (1996a). Plasma HVA in adults with mental retardation and stereotyped behavior: Biochemical evidence for a dopamine deficiency model. *American Journal on Mental Retardation, 100*, 413–427.

Lewis, M. H., Gluck, J. P., Bodfish, A. J., & Mailman, R. B. (1996b). Neurobiological basis of stereotyped movement disorder. In R. Sprague & K. Newell (Eds.), *Stereotypies: Brain- behavior relationships* (pp. 37–67). Washington, DC: American Psychological Association.

Lewis, M., MacLean, W. E., Johnson, W. L., & Baumeister, A. A. (1981). Ultradian rhythms in stereotyped and self-injurious behavior. *American Journal of Mental Deficiency, 85*, 601–610.

Lindsey, J. K. (1999). *Models for repeated measurements* (2nd ed.). New York: Oxford University Press.

Liss, M., Saulnier, C., Fein, D., & Kinsbourne, M. (2006). Sensory abnormalities in autistic spectrum disorders. *Autism, 10*, 152–172.

Loftin, R. L., Odom, S. L., & Lantz, J. F. (2008). Social interaction and repetitive motor behaviors. *Journal of Autism and Developmental Disorders, 38*, 1124–1135.

Lourie, R. S. (1959). The role of rhythmic patterns in childhood. *American Journal of Psychiatry, 105*, 653–660.

Lovaas, I. O., Litrownik, A., & Mann, R. (1971). Response latencies to auditory stimuli in autistic children engaged in self-stimulatory behavior. *Behavior Research and Therapy, 9*, 39–49.

Lovaas, I. O., Newsom, C., & Hickman, C. (1987). Self-stimulatory behavior and perceptual reinforcement. *Journal of Applied Behavior Analysis, 20*, 45–68.

Mace, F. C., & Belfiore, P. (1990). Behavioral momentum in the treatment of escape-motivated stereotypy. *Journal of Applied Behavior Analysis, 23*, 507–514.

MacLean, W. E., Bryson-Brockmann, W., Arendt, R., Beck, B., Fidler, P. S., & Baumeister, A. A. (1984). Time-series analysis of stereotyped movements: Relationship of body-rocking to cardiac activity. *American Journal on Mental Deficiency, 89*, 287–294.

Mason, G. J. (1991). Stereotypies: A critical review. *Animal Behaviour, 41*, 1015–1037.

Mathie, M. J., Coster, A. C. F., Lovell, N. H., & Celler, B. G. (2004). Accelerometry: Providing an integrated, practical method for long-term, ambulatory monitoring of human movement. *Physiological Measurement, 25*, 1–20.

Matson, J. L., & Nebel-Schwalm, M. (2007). Assessing challenging behaviors in children with autism spectrum disorders: A review. *Research in Developmental Disabilities, 28*, 567–578.

Militerni, R., Bravaccio, C., Falco, C., Fico, C., & Palermo, M. T. (2002). Repetitive behaviors in autistic disorder. *European Child and Adolescent Psychiatry, 11*, 210–218.

Minnen, D., Westeym, T, Ward, J. A., & Lukowicz, P. (2006). Performance metrics and evaluation issues for continuous activity recognition. In *Proceedings of performance metrics for intelligent systems* (*PerMIS*). Gaithersburg, MD.

Moss, J., Oliver, C., Arron, K., Burbidge, C., & Berg, K. (2009). The prevalence and phenomenology of repetitive behavior in genetic syndromes. *Journal of Autism and Developmental Disorders, 39*, 572–588.

Munguia-Tapia, E., Marmasse, N., Intille, S. S., & Larson, K. (2004). MITes: Wireless portable sensors for studying behavior. In *Proceedings of extended abstracts ubicomp 2004: Ubiquitous computing*.

Nagin, D. (1999). Analyzing developmental trajectories: A semi-parametric, group-based approach. *Psychological Methods, 4*, 139–157.

Newell, K. M., & Bodfish, J. W. (2007). Dynamical origins of stereotypy: Relation of postural movements during sitting to stereotyped movements during body-rocking. *American Journal on Mental Retardation, 112*, 66–75.

Newell, K. M., Incledon, T., Bodfish, J. W., & Sprague, R. L. (1999). Variability of stereotypic body-rocking in adults with mental retardation. *American Journal on Mental Retardation, 104*, 279–288.

Newell, K. M., van Emmerick, R. E. A., Lee, D., & Sprague, R. L. (1993). On postural stability and variability. *Posture and Gait, 4*, 225–230.

Pena, D., Tiao, G. C., & Tsay, R. S. (2001). *A course in time series analysis*. New York: Wiley.

Pyles, D. A. M., Riordan, M. M., & Bailey, J. S. (1997). The stereotypy analysis: An instrument for examining environmental variables associated with differential rates of stereotypic behavior. *Research in Developmental Disabilities, 18*, 11–38.

Rapp, J. T., & Vollmer, T. R. (2005). Stereotypy II: A review of neurobiological interpretations and suggestions for an integration with behavioral methods. *Research in Developmental Disabilities, 26*, 548–564.

Repp, A. C., Karsh, K. G., Deitz, D. E. D., & Singh, N. N. (1992). A study of the homeostatic level of stereotypy and other motor movements in persons with mental handicaps. *Journal of Intellectual Disability Research, 36*, 61–75.

Ridley, R. M. (1994). The psychology of perseverative and stereotyped behaviour. *Progress in Neurobiology, 44*, 221–231.

Ridley, R. M., & Baker, H. F. (1982). Stereotypy in monkeys and humans. *Psychological Medicine, 12*, 61–72.

Rojahn, J., Matlock, S. T., & Tasse, M. J. (2000). The stereotyped behavior scale: Psychometric properties and norms. *Research in Developmental Disabilities, 21*, 437–454.

Rutter, M. (1996). Autism research: Prospects and progress. *Journal of Autism and Developmental Disorders, 26*, 257–275.

Schopler, E., Reichler, R. J., & Renner, B. R. (1986). *The childhood autism rating scale*. New York: Irvington.

Schultz, T., & Berkson, G. (1995). Definition of abnormal focused affections and exploration of their relation to abnormal stereotyped behaviors. *American Journal of Mental Retardation, 100*, 376–390.

Sprague, R. L., & Newell, K. M. (Eds.). (1996). *Stereotyped movements: Brain and behavior relationships*. Washington, DC: American Psychological Association.

Sprague, R. L., van Emmerik, R. E. A., Slobounov, S. M., & Newell, K. M. (1996). Facial stereotypic movements and tardive dyskinesia in a mentally retarded population. *American Journal on Mental Retardation, 100*, 345–358.

Symons, F. J., Sperry, L. A., Dropik, P. L., & Bodfish, J. W. (2005). The early development of stereotypy and self-injury: A review of research methods. *Journal of Intellectual Disabilities Research, 49*, 144–158.

Thelen, E. (1981). Rhythmical behavior in infancy: An ethological perspective. *Developmental Psychobiology, 17*, 237–257.

Turner, M. (1999). Annotation: Repetitive behaviour in autism: A review of psychological research. *Journal of Child Psychology and Psychiatry, 6*, 839–849.

van den Berg-Emons, H. J., Bussmann, J. B., Balk, A. H., & Stam, H. J. (2000). Validity of ambulatory accelerometry to quantify physical activity in heart failure. *Scandinavian Journal of Rehabilitation Medicine, 32*, 187–192.

van Emmerick, R. E. A., Sprague, R. L., & Newell, K. M. (1993a). Arm tremor, tardive dyskinesia, and developmental disability. *American Journal on Mental Retardation, 98*, 74–83.

van Emmerick, R. E. A., Sprague, R. L., & Newell, K. M. (1993b). Finger tremor and tardive dyskinesia. *Experimental and Clincial Psychopharmacology, 1*, 259–268.

Varni, J. W., Lovaas, O. I., Koegel, R. L., & Everett, N. L. (1979). An analysis of observational learning in autistic and normal children. *Journal of Abnormal Child Psychology, 7*, 31–43.

Velicer, W. F., & Fava, J. (2003). Time series analysis. In J. A. Schinka & W. F. Velicer (Eds.), *Handbook of psychology: Research methods in psychology* (Vol. 2, pp. 581–606). New York: Wiley.

Vollmer, T. R. (1994). The concept of automatic reinforcement: Implications for behavioral research in developmental disabilities. *Research in Developmental Disabilities, 15*, 187–207.

Ward, J. A., Lukowicz, P., & Troster, G. (2006). Evaluating performance in continuous context recognition using event-driven error characterisation. In *Proceedings of the international workshop in location and awareness (LoCA)*, Dublin, Ireland, pp. 239–255.

Watkins, K. M., & Konarski, E. A. (1987). Effect of mentally retarded persons' level of stereotypy on their learning. *American Journal of Mental Deficiency, 91*, 361–365.

Weinberg, H., & Lemaire, C. (1998). *Using the ADXL202 accelerometer as a multi-function sensor (tilt, vibration and shock) in car alarms (Technical Note)*. Norwood, MA: Analog Devices.

Welk, G. J. (2002). Introduction to physical activity research. In G. J. Welk (Ed.), *Physical activity assessments for health-related research* (pp. 3–18). Champaign, IL: Human Kinetics Publishers, Inc.

Westeyn, T., Vadas, K., Bian, X., Starner, T., & Abowd, G. D. (2005). Recognizing mimicked autistic self-stimulatory behaviors using HMMs. In *Proceedings of the ninth IEEE international symposium on wearable computers* (pp. 164–169).

Witten, I. H., & Frank, E. (1999). *Data mining: Practical machine learning tools and techniques with java implementations*. San Francisco, CA: Morgan Kaufmann.

Wyatt, D., Philipose, M., & Choudhury, T. (2005). Unsupervised activity recognition using automatically mined common sense. In *Proceedings of the twentieth national conference on artificial intelligence* (pp. 21–27). Menlo Park, CA: AAAI Press.