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A Comparison of Measurement Systems to Score Sleep Disturbance for Children With Autism Spectrum Disorders

Aaron Lesser
University of Nebraska Medical Center

A COMPARISON OF MEASUREMENT SYSTEMS TO SCORE SLEEP DISTURBANCE FOR CHILDREN WITH AUTISM SPECTRUM DISORDERS

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Aaron David Lesser, Ph.D., BCBA

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University of Nebraska Medical Center

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Supervisory Committee:

Kevin C. Luczynski, Ph.D., BCBA-D

Wayne W. Fisher, Ph.D., BCBA-D

Nicole M. Rodriguez, Ph.D., BCBA-D

Valerie M. Volkert, Ph.D., BCBA-D

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Aaron D. Lesser, Ph.D.

University of Nebraska Medical Center, 2015

Advisor: Kevin C. Luczynski, Ph.D.

Direct observation of children's sleep disturbance in the home is critical to understanding child behavior while awake and determining qualitative features of the sleep environment, but obtaining these data from an in-home recorded video, second-by-second, is impractical in terms of scoring time because observers score when the child is asleep and awake. In Studies 1 and 2, we conducted an analog study to assess a motion-detection camera to determine whether it would be suitable to measure children's sleep disturbance. In Study 3, we obtained in-home measures of sleep disturbance for three children with an autism spectrum disorder using a motion-detection, momentary-time sampling (MTS), and actigraphy measurement system and compared the accuracy to a continuous, second-by-second, measurement system. We also recorded the time required to score each night of sleep disturbance and assessed social acceptability of the measurement systems. Results support the use of MTS 10-min as an accurate, efficient, and acceptable measurement system for scoring sleep disturbance. Implications for practice include obtaining videos from the home and scoring sleep disturbance on a nightly basis.

Keywords: autism spectrum disorder, delayed sleep onset, direct observation, dyssomnia, efficiency, in-home video recording, measurement, momentary-time sampling, motion detection, sleep disturbance, sleep onset latency, telehealth

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A Comparison of Measurement Systems to Score Sleep Disturbance for Children with Autism Spectrum Disorders

Sleep is considered a critical bodily state that supports cognitive and physical development and energy restoration, especially early in one's life. Children that experience problems with timing, quality, and quantity of sleep are diagnosed with a sleep disorder (American Psychological Association, 2013). Primary sleep disorders are not accompanied with medical conditions, substance abuse, or other mental disorders (Anders & Eiben, 1997; Buscemi et al., 2005). Primary sleep disorders are classified by dyssomnias and parasomnias, and the former represents two primary types of sleep disorders that young children experience, which involve difficulty initiating sleep (i.e., named either delayed sleep onset, sleep onset delay, or sleep onset latency) and waking for extended periods during the night (i.e., wakings after sleep onset [nighttime awakenings]) (Cohen, Conduit, Lockley, Rajaratnam, & Cornish, 2011; Krakowiak, Goodlin-Jones, Hertz-Picciotto, Croen, & Hansen, 2008; Kuhn, 2014; Williams, Sears, & Allard, 2004). Dyssomnias are distinguished between intrinsic (inside the body) and extrinsic (outside the body) determinants of sleep problems, and the subtypes of extrinsic dyssomnias include limit-setting, sleep-onset association, or combined type (Kuhn, 2014; Meltzer & Mindell, 2008). Children with limit-setting type remain awake beyond the desired bedtime but may sleep through the night (greater sleep onset latency), and children with sleep-onset association type awaken multiple times, sometimes for extended durations, during the night (wakings after sleep onset). Children that experience these two types of sleep disturbance do not achieve the recommended duration of sleep, based on developmental normative data (Mindell, Kuhn, Lewin, Meltzer, & Sadeh, 2006).

Sleep disturbance negatively affects important domains in a child's life, and affects neurotypical children and children with disabilities across demographic boundaries (Byars, Yolton, Rausch, Lanphear, & Beebe, 2012; Richdale, 1999). Between 10-35% of all children experience a form of sleep disturbance, and these figures remain largely unchanged in last 35 yr (e.g., Anders, 1979; Byars, et al., 2012; France & Blampied, 1999; Mindell et al., 2006; Owens, 2008; Richman, 1981). Up to 86% of children with disabilities or an autism spectrum disorder (ASD) experience sleep problems (Didden & Sigafoos, 2001; Liu, Hubbard, Fabes, & Adam, 2006; Polimeni, Richdale, & Francis, 2005; Richdale & Schreck, 2009; Souders et al., 2009). As a related concern, sleep problems can develop before 1 yr of age (Carey, 1974; Sadeh, 2004) and persist if untreated (Gregory & O'Connor, 2002; Kataria, Swanson, & Trevathan, 1987). These prevalence data are important because they show how many children are affected and how early in life sleep problems can develop.

For children of typical development, there are moderate positive correlations between sleep disturbance and poor daytime functioning such as worsening in cognitive and attention skills (Sadeh, Gruber, & Raviv, 2002; Wolfson & Carskadon, 1998), academic underachievement (Curcio, Ferrara, & De Gennaro, 2006; Dewald, Meijer, Oort, Kerkhof, & Bögels, 2010), and daytime sleepiness (Fallone, Owens, & Dean, 2002). For children with disabilities, including ASDs, sleep disturbance can worsen the frequency and intensity of problem behavior (Kennedy & Meyer, 1996), problems related to feeding (Reed, Dolezal, Cooper-Brown, & Wacker, 2005), and the severity of symptoms of an ASD (Schreck, Mulick, & Smith, 2004). It is likely, for these reasons, that pediatric sleep disturbance is among the top five complaints raised by parents to their child's healthcare provider (Arndorfer, Allen, & Aljazireh, 1999; Mindell & Owens, 2003; Owens, 2001). Thus, successful treatment of sleep disturbance may reduce maladaptive behavior and improve and enhance learning opportunities during the day. In addition to the direct effects of sleep disturbance on children's functioning, caregivers of these children report higher rates of maternal depression and marital discord (Bell & Belsky, 2008; Chavin, & Tinson, 1980; Richman, 1981) and poor sleep quality (Meltzer & Mindell, 2007). Moreover, Owens (2005) suggested poor parental sleep may be a risk factor for child abuse. Thus, addressing sleep disturbance may benefit the parents and children by increasing total sleep for both parties, reducing parental stress (Hodge, Hoffman, Sweeney, & Riggs, 2013), improving daytime functioning (Meltzer & Mindell), and improving and potentially preventing psychopathologies such as depression (Hiscock, Bayer, Hampton, Ukoumunne, & Wake, 2008).

Sleep disturbance that does not result from an underlying medical condition is amenable to a behavioral analysis of the environmental variables influencing sleep (Blampied & France, 1993). Initiating sleep is a behavior – a learned skill – that follows a period of behavioral quietude and is influenced by motivation (sleep pressure) and environmental stimuli (sleep dependencies) (Blampied & Bootzin, 2013; Blampied & France; Bootzin, 1977; France & Blampied, 1999). Thus, sleep disturbance occurs when events compete with motivation to sleep (e.g., watching a preferred video, playing with a game, playing with a caregiver or sibling), environmental cues that should occasion sleep are absent or have not been established (e.g., stuffed animal, white noise, child's bed), or both. Treatments based on the principles of learning theory have been shown to be effective, and there is strong empirical support (Mindell et al., 2006). Stimulus control is one principle of learning theory and is defined by the occurrence of a specific behavior in the presence of certain cues (Catania, 1998). Behavioral treatments based on establishing proper stimulus control and eliminating sources of reinforcement for remaining awake may be advantageous compared to a synthetic hormone (e.g., melatonin) or a prescription drug treatment (e.g., clonazepam) because after stimulus control is established, and the child learns how to engage in behavioral quietude, the child can independently initiate sleep under the appropriate conditions. Moreover, the effects of stimulus control are likely to maintain and do not require daily drug administration to maintain treatment efficacy (National Sleep Foundation, 2014).

Directly observing the child when awake at bedtime and throughout the night can lead to the identification of variables that contribute to sleep onset latency and wakings after sleep onset; this information is important because the selection and design of a treatment is linked to the environmental variables influencing the sleep disturbance. Mindell and Durand (1993) used in-home video recordings of six children’s bedtime routines to obtain qualitative information on events that influenced sleep disturbance. For three of the six children, the researchers observed the parents routinely give a bottle prior to bedtime and, based on this information, they designed a treatment that included withholding the bottle at bedtime. For other children (the number was not specified), the researchers observed the parents rock their children to sleep. The video recordings were also useful in that they allowed the researches to obtain direct, objective measures on procedural fidelity by observing whether parents withheld the bottle or rocked their children during the prescribed period before bedtime.

In another application, Jin, Hanley, and Beaulieu (2013) used in-home video recordings to measure competing activities and identify undesirable sleep dependencies at bedtime *and* throughout the entire night for three participants. For Walter, parental and sibling attention, and access to books or magazines influenced sleep onset latency. During treatment, the researchers instructed parents to provide access to these putative reinforcers for 20 min prior to bedtime, and after bedtime these stimuli were restricted and if he left his room, parents re-directed him to his room and did not engage in extensive conversation. Andy's sleep onset latency was affected by behavior that allowed him to access putative automatic reinforcement (e.g., manipulating clothing items, singing). To mitigate the problem, the researchers instructed parents to allow Andy access to these items for 30 min prior to bedtime to decrease the value of these items when he attempted to initiate sleep. Andy also initiated sleep with a CD player that his parents turned on at bedtime, but turned off after he initiated sleep. Thus, when Andy exhibited wakings after sleep onset, he could not re-initiate sleep. As a result, parents were instructed to eliminate the CD player at bedtime and throughout the night. For Lou, parental attention and access to tangible items competed with sleep initiation, thus, the researchers observed elevated levels of sleep onset latency. To address parental attention interfering with sleep onset, the researchers implemented scheduled (time-based) visits to eliminate the relation between the child's bids for attention and the parent visiting the room, and a bedtime clean-up routine to remove access to tangible items. Taken together, researchers have directly observed children's sleep hygiene[1] in their home to identify environmental variables that interfere with motivation to sleep and to identify undesirable sleep dependencies throughout the night. This is important because sleep dependencies at bedtime may be different than those present throughout the night (see Andy as an example). In turn, information obtained from videos is helpful to develop individualized treatments and monitor procedural fidelity.

Researchers have obtained direct observations of sleep disturbances by being physically present (face-to-face) in children's bedrooms. The use of face-to-face in-home observations have typically been conducted with infants (Thoman, 1975, 1990; Thoman & Acebo, 1995). Thoman (1990) noted that these observations have been limited to 7 hr during the daytime because of practicality and funding, but she cited the need for 24 hr recordings to obtain a complete account of a child's sleep patterns. However, as detailed by Sadeh (2015), concerns related to repeatedly traveling to a family's home and issues related to the reactivity effects of an observer present during the child's bedtime routine are challenges to face-to-face, in-home observations. Another issue is that an observer must be available at the home to record the child's sleep patterns. As one solution to minimize reactivity, Jin, Hanley, and Beaulieu (2013) used a video camera to obtain recordings in the child's bedroom. However, obtaining several hours or an entire night of video, presents the practical challenge of efficiently culling periods of the night when the child exhibits sleep disturbance to gather qualitative measures of the sleep environment.

[1] Sleep hygiene is a term used to describe procedures toward establishing healthy sleep habits by maintaining motivation, developing predictable environmental stimuli in the child's bedroom, and guarding against maladaptive sleep dependencies (France & Blampied, 1999; Mindell, Meltzer, Carskadon, & Chervin, 2009).

An infrared motion-detection camera that automatically produces video clips only when there is child movement throughout the night would eliminate the time associated with manually identifying these periods. That is, starting at the child's desired bedtime and ending at the child's wake time, the camera would produce videos of only child movement that would be subsequently viewed and scored by an observer. If the camera was accurate at recording movement that also meets the direct-observation definition of a child being awake, the total duration that the child was awake and asleep could be quickly calculated by simply adding the durations of all the video clips. Moreover, sleep researchers and clinicians could obtain common dependent measures of interest, such as duration of sleep onset latency, number of wakings after sleep onset, duration of wakings after sleep onset, number of times the child leaves the bedroom, and number of parent visits (e.g., Anders, 1979; France & Hudson, 1990; Meltzer & Mindell, 2007; Owens, 2001; Sadeh, Raviv, & Gruber, 2000). Furthermore, and arguably as important, measures on procedural fidelity could be obtained from the video clips. In summary, an automated, accurate motion-detection camera would permit the collection of qualitative features of the sleep environment and quantitative measures of sleep and sleep disturbance.

With advances in technology over recent years, research groups have been providing services to individuals located in remote and rural locations and to individuals without the time and financial resources to travel to a sleep clinic. A telehealth (web-based delivery) model provides an opportunity for experts to assess and treat socially important challenging behavior in the context where it most often occurs (e.g., home and school) and involves installing a camera in that location. Using a video camera without an internet connection to obtain measures requires parent involvement to turn on and off the camera, unless a preset timer is used (Higley & Dozier, 2009). This method requires frequent visits to the child's home to gather recorded videos, which could result in delayed data collection and, thus, treatment decisions. An internet-connected camera addresses the aforementioned limitations in that parent involvement is not required because the camera power settings can be controlled without physical presence in the home. Remote access also allows the nightly transfer of videos from the child's home to the data collector's laptop, and the transfer of the video can be securely achieved using a virtual private network (VPN) with encryption. As a result, state-of-the-science services can become available to families with a child who exhibits sleep disturbance regardless of their geographic location. Direct measurement of sleep, remotely, and without parent involvement in the transfer of video, answers Blampied's (2013) call-to-action by using internet technology for the assessment of in-home sleep disturbance. In addition, in-home measures of sleep disturbance, as opposed to measures obtained in a laboratory, are likely to provide the most representative account of sleep because environmental conditions are similar across nights (Ancoli-Israel, Kripke, Mason, & Messin, 1981). Given the applied implications of an internet-connected motion-detection camera system, we assessed in Study 1 the accuracy of a motion-detection camera in a controlled, analog setting to systematically evaluate its precision and reliability to detect motion and to learn what variables affect motion detection. Then, we assessed, in Study 2, the generality of the motion-detection measurement system to a variety of human movements in a controlled, analog setting.

A motion-detection camera can automatically record periods of movement; if it is accurate, it could be used to quantify the duration of sleep and sleep disturbance throughout a night (in addition to gathering qualitative information). For this reason, the accuracy of the motion-detection camera should be compared to a direct-observation measurement system that involves a continuous (second-by-second) record and the savings in scoring time (i.e., efficiency) produced by the camera should be analyzed. Furthermore, the accuracy and efficiency of the motion-detection measurement system should be compared to other systems that have been used to measure sleep in the home.

Momentary-time sampling (MTS) is a discontinuous measurement system with direct observation and it involves observing behavior for a period of time at specified intervals (i.e., systematic observation sampling) to quantify sleep disturbance throughout the night. As a result, less time is required to score the entire night compared to a continuous (second-by-second) measurement system. Researchers have applied MTS via face-to-face observations at the scheduled intervals and video records. For example, Piazza and Fisher (1991) and Piazza, Fisher, and Sherer (1997) conducted face-to-face observations using a 30-min MTS interval to score sleep disturbance for young children and adolescents in a hospital setting. Jin, Hanley, and Beaulieu (2013) extended Piazza et al. (1997) by applying a 30-min interval recorded video of children in their bedroom. In a measurement comparison, Jin, Hanley, and Haskell (2013) evaluated a 5-, 10-, 30-, 60-, and 120-min intervals compared to a continuous video and the outcomes indicated that 5- and 10-min intervals for sleep onset and a 30-min interval for wakings after sleep onset produced the least amount of error. These groups of researchers likely selected the 30-min interval to minimize observation time, but the researchers did not report efficiency measures. The time savings of MTS compared to scoring an entire night on a second-by-second basis increases the practicality of researchers or clinicians to score sleep disturbance on a daily or weekly basis. Because MTS is a discontinuous measurement system, sleep disturbance may be underestimated compared to a second-by-second account of the child's night depending on the whether sleep disturbance occurs during or between observation intervals. On the other hand, measures of sleep disturbance may be overestimated if sleep disturbance consistently occurs during the observation interval because the amount is calculated based on the number of intervals the child is awake, multiplied by the size of interval. Therefore, the duration and frequency of sleep disturbance, and observation interval size directly affect overestimation and underestimation measures (Harrop & Daniels, 1986). Given the increase in efficiency and precedence of using MTS to measure sleep, including MTS to obtain sleep disturbance measures throughout the night and to determine the time required to obtain those measures would contribute to the research on sleep measurement.

The American Academy of Sleep Medicine recommends the use of actigraphy as the primary method to measure sleep patterns and determine a child's response to treatment (Morgenthaler et al., 2007). Actigraphy is an activity-based (movement-based) measurement system that records movement in epochs, which is the unit of time (typically one min), via an accelerometer affixed to the individual's dominant or nondominant wrist (Paavonen, Fjällberg, Steenari, & Aronen, 2002; Sadeh, Sharkey, & Carskadon, 1994). After recording movement, an algorithm, comprised of several variables[2], is applied to provide a quantitative account of the duration of sleep and awake.

[2] The variables used in the algorithm developed by Sadeh, Sharkey, and Carskadon (1994) include (a) the mean number of activity counts during the scored epoch and the five epochs before and after the scored epoch, (b) the standard deviation of the activity counts during the scored epoch and the five epoch before it, (c) the number of epoch with activity equal to or higher than 50 but less than 100 during the scored epoch and the five epochs before and after the scored epoch, and (d) the natural logarithm of the number of activity counts during the scored epoch plus one.

Moreover, whether quantitative measures obtained from a motion-detection camera are accurate compared to actigraphy has yet to be evaluated.

At present, the measurement system that provides accurate quantitative measures is unknown. Moreover, there are no published data on the time required to obtain sleep disturbance measures. For this reason, in Study 3 we compared the accuracy and efficiency of three direct-observation measurement systems and actigraphy to a continuous measurement system (the criterion record) to inform measurement of in-home sleep disturbance in research and practice. To determine whether an applied problem has been resolved is to seek a response from the individuals that determine social importance (Wolf, 1978). Likewise, the responses from these individuals may indicate whether they will continue to implement a system (e.g., treatment procedures) in the absence of researchers. As this relates to measurement of sleep, measurement systems that families prefer are more likely to be integrated in the home and adopted into practice. For this reason, we also assessed social acceptability for the use of a nighttime video camera and actigraphy in children's homes.

Study 1

The applied implication of the motion-detection camera is to automatically record an individual's movement in their beds throughout the night. As a pre-requisite to this application, the extent to which the size of movements, the percentage of the detection window changed by movements, or both influence the detection of motion should be evaluated. We evaluated the accuracy of the camera in a series of analog assessments. In addition, we evaluated the extent to which artificial light (i.e., 4W nighttime light) and bedroom objects (e.g., furniture, toys) affected the accuracy of motion detection.

Method

Setting, camera setup, and materials. The motion-detection camera was assessed in an empty room (2.7 m by 3.4 m) with no windows; the position of the camera, infrared light, and the angle-of-view from the camera are depicted in Figure 1. An Axis P-1344 internet-protocol camera equipped with motion-detection software and infrared capability was used to detect programmed movements, and the camera was positioned at a height of 2.4 m. An Axton AT-7 940-nm infrared light source provided supplementary illumination, and the device was positioned at the same height as the camera but the direction of the light was opposite to the direction of the camera. The camera had a wide angle lens with a focal length of 3 mm to 8 mm and a horizontal angle-of-view of 27 - 66°, which is sufficient to observe a 1.0- by 0.8-m room (8 mm) up to a 2.7- by 3.6-m room (3 mm). To maximize the viewing area, the lens was set at 66°.

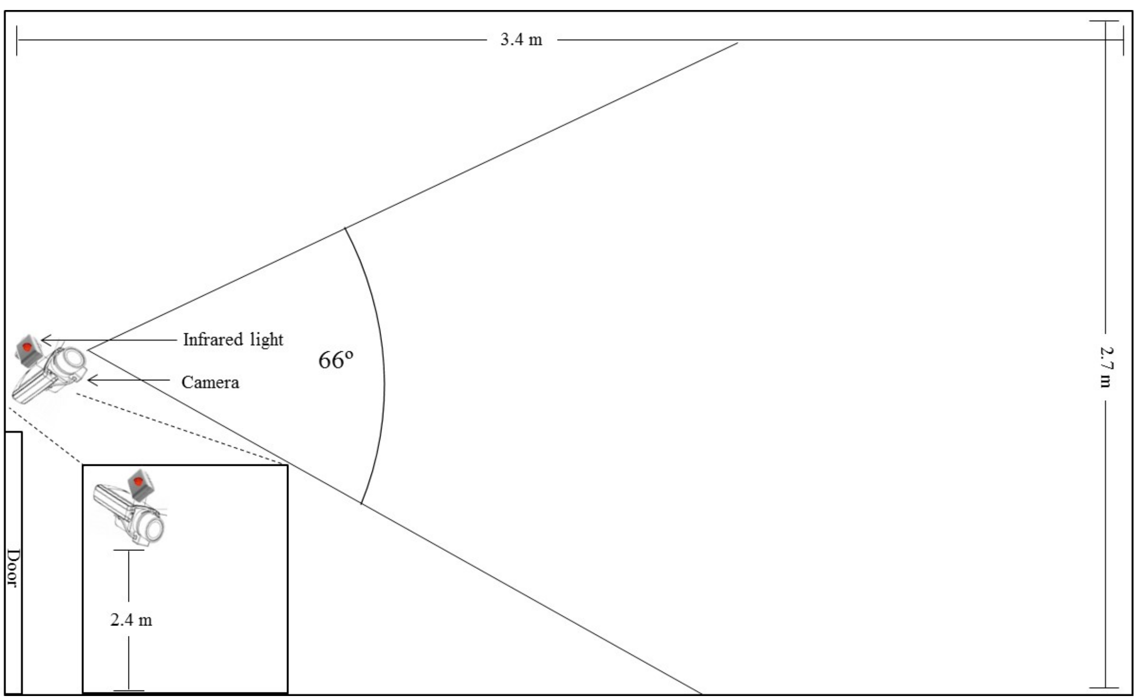

Figure 1. A scaled-schematic of the room arrangement in Studies 1 and 2.

We used different sized cardboard boxes[3] to evaluate whether the size of movements, percentage of the area of the video that movements comprised, or both, influenced the detection of motion. We used artificial objects in the form of cardboard boxes, rather than natural objects such as different sized human movements, due to the ease with which the dimensions of the box could be modified and the precision with which the boxes could be moved into the video during the assessments. We assessed four different box sizes to approximate different human movements that vary in size. Each box had a height of 12 in and a depth of 24 in, but only the horizontal surface of the box could be seen from the camera. The horizontal surfaces of the boxes were 6 in (15 cm), 12 in (30 cm), 24 in (60 cm), and 32 in (91 cm). Metal guide rails, shown in Figure 2, similar to rails used for utility drawers, were affixed to the boxes. These rails allowed us to move the boxes into the view of the camera in precise increments.

[3] We purchased 12 in boxes from Uline (Pleasant Prairie, WI), and we created each box size.

Figure 2. This image shows the 12-in box with rails attached to each side that allowed for precise movements.

During the course of the study, we recorded the light level in the room at the position of the camera lens using a light meter (Mastech Digital Illuminance LX 1330B). The device can detect light levels between 0 and 200,000 lux. For example, a moonlit, cloudy night is equivalent to 0.1 lux, one candle flame emits 10.7 lux, and sunshine approaches 100,000 lux.

Camera settings and motion-detection software settings. There are two groups of settings that can be changed (see Table 1): camera settings and motion-detection settings. Camera settings affect the image prior to video production. For example, exposure is a setting that affects the amount of light that reflects on the camera's image sensor, and the setting in the camera is accessible from any internet browser.

Motion-detection software settings affect whether motion is detected and a video clip is produced. The motion-detection software settings were accessible from the manufacturer's native software client, Axis Camera Station[4] (the free program is available at www.axis.com). Operational definitions for each motion-detection software setting are based on the user-manual provided by the manufacturer (we confirmed these definitions during our initial, informal experience with the camera).

The *detection window*[5] was a square-shaped region (there is no option for an irregular-shaped region) of the video feed designated to detect motion. The size of the detection window can be changed to encompass any percentage of the video feed. Only motion that occurs within the detection window is eligible for detection; motion that occurs outside the detection window cannot be detected. When motion is detected, the camera records the entire video feed, not just the area in the detection window. *Object-size* is defined as the proportion of pixels that a movement must change within the active window to be detected as motion. A high value is used to detect the movement of large objects (e.g., people and vehicles); a low value is used to detect the movement of small objects (e.g., birds and mice). S*ensitivity* is defined by the difference in contrast between the background and the object producing the movement. With a high value, ordinary colored objects on ordinary backgrounds are detected. With a low value, only bright

[4] We made all changes to the motion-detection settings in Axis Camera Station, but all settings can be changed from an Internet browser.
[5] The original name of this setting is named the *active window* as stated by the manufacturer. We chose to change the name to *detection window* to avoid confusion with the *activity monitor* described later.

objects on dark backgrounds are detected. Object-size and sensitivity range from 0 to 100, although the values do not represent a unit of measurement (e.g., object-size of 1 does not equate to 2.54 cm). *History* defines the number of pixels that comprise motion that can change before the motion is considered nonmotion. With a lower value, the motion in each recorded video clip will comprise a smaller number of pixels, which can result in multiple video clips of the same movement. With a high value, the motion in each recorded video clip will comprise a larger number of pixels, which can result in a single video clip for a single bout of movement.

Other settings affect the duration and number of video clips, but they are unrelated to the detection window, object-size, sensitivity, and history. A *pre-buffer* is a specified period of time prior to the detected movement that is added to the video clip of motion. A *post-buffer* is a period of time following the end of a detected movement that is added to the end of the video clip of motion. Each of the buffers range from 0 to 60 s and operate independently of each other such that each buffer can be set at a different duration. For example, if a 5-s pre-buffer and a 10-s post-buffer were set and the duration of motion lasts for 10 s, the camera would add 5 s that occurred prior to the detected motion and 10 s after the motion ended, producing a 25-s video clip. A *trigger-period* refers to the period of time that must elapse before the camera will detect a new movement. Essentially, the trigger- period is considered the minimal inter-recording interval between movements.

Table 1

Categories of Variables that Influence Motion-Detection

Variables	Operational Definition
Motion-Detection Camera	
1. Detection Window	The area of the video in which motion can be detected.
2. Object-Size (0 – 100)	The proportion of pixels in the detection window that must change for motion to be detected.
3. Sensitivity (0 – 100)	The level of contrast between the moving object and background per pixel.
4. History (0 – 100)	The amount of pixels that can change so the camera continues to detect the same movement.
5. Pre-buffer (0 – 60 s)	The period of time prior to the movement added to the beginning of the video clip.
6. Post-buffer (0 – 60 s)	The period of time following the movement added to the end of the video clip.
7. Trigger-Period (0 – 60 s)	The period of time that must elapse before motion can be detected.
In-Room Arrangement	
8. Position of Infrared (IR) Light	The infrared illuminator was positioned away from the viewing area, toward a wall.
9. Number of Items in Detection Window	Objects that may be found in a child's bedroom that varied in size, shape, and color were added during the assessments that involved multiple objects.
10. Artificial and Natural Light	An Axton 940 nm infrared illuminator and a Leviton 4W manual nightlight.
Camera Variables	
11. Exposure (0 – 100)	Shutter speed, aperture, and ISO influence the amount of artificial and natural light that enters the lens.
12. IR Cut Filter	A filter that allows the transmission of IR through the lens and the image sensor.

Calibrating the motion-detection software to enhance precision. When calibrating the motion-detection software settings using Axis Camera Station, detected motion is displayed in realtime as an area plot in the activity monitor, and the height and width of the area plot is affected by the magnitude and duration of motion, respectively. The area plot depicts the last 50 s of motion and continuously updates.

In the activity monitor, a horizontal line depicts the object-size value (0 to 100). A value of 0 places the line at the bottom of the activity monitor, so that any detected motion meets the object-size requirement. A value of 100 places the line at the top of the activity monitor, so only motion that meets the object-size requirement is detected. Thus, object-size affects motion detection because motion above the line, denoted by a red-area plot, is recorded (produces a video clip), and motion below the line, denoted by a blue-area plot, is not recorded. For our purpose of detecting small movements, object-size values at the low end of the continuum is desired (i.e., zero to five). In addition to the size of movements influencing the height of the area plot in the activity monitor, the sensitivity value affects the depicted height of the detected motion, with lower values decreasing the height and higher values increasing the height. For our purpose of detecting small movements, a sensitivity value at the high end of the continuum is desired (i.e., 90 to 100).

In summary, object-size and sensitivity, jointly, determine what motion is detected and recorded, and are critical to the calibration process for these reasons. These variables were consistent with other free, commercially available motion-detection software programs, although the range of values for each setting may be different (e.g., Webcam Motion Detector, available from www.zebra-media.com, Zone Trigger, available from www.zonetrigger.com, and Aimetis Symphony, available from www.aimetis.com).

Prior to conducting formal assessments with the camera, we conducted a no-motion (control) recording for 5 min with sensitivity at 100. During this recording, a researcher with a laptop computer was in the room (not in the view of the camera), no objects were in the room, and the room was dark (the light level was 0.0 lux). That is, we did not program any motion. We expected that no video clips would be produced; however, 53 clips with durations of less than 2 s were produced across the 5 min. We reviewed each clip and did not observe any motion. Nevertheless, because video clips were produced, the camera detected motion that was not observable by the human eye. The reason the software detected motion is because of electromagnetic “noise,” which is a known issue related to no- and low-light level videography and photography. We considered these video clips false-positive outcomes because the video clips did not contain observable movement.

Because we knew that sensitivity affected the height of detected motion, we lowered the sensitivity value below 100 and we noticed a reduction in the height of the area plot of the electromagnetic “noise.” By lowering the sensitivity value so that detected “noise” was minimal, and a consistent height of the “noise” was observed, and by increasing the object-size value to a value above the height of the “noise,” we hypothesized that the camera would detect and record only observable movement, eliminating false-positive video clips. To calibrate the motion-detection software settings in a technological manner, we developed a calibration procedure to maximize the precision of the motion-detection software.

The calibration procedure involved systematically changing object-size and sensitivity and observing the activity monitor. First, prior to each session, the room was arranged per the conditions of a given session, and no movements was programmed.

Second, sensitivity was set at the highest value of 100, and we observed the activity monitor for 100 s; if motion was detected, we lowered the sensitivity value by one value (i.e., 99), and continued to decrease the values until no motion was detected (e.g., 94) for 100 s (equivalent to two times the duration of activity monitor in Axis Camera Station). Third, we increased the sensitivity value by one unit (e.g., 95) and observed the activity monitor for 100 s to ensure that the electromagnetic "noise" remained at a minimal, consistent height. The reason we chose a value that allowed some electromagnetic "noise" to be detected in the activity monitor, rather than using a lower sensitivity value that eliminated the "noise," was that we were concerned that the ability of the camera to detect small observable movements would be negatively affected with lower sensitivity values. Fourth, object-size was set to a value above the height of the area plot of the electromagnetic noise observed during a 100-s period. Fifth, we observed for another 100-s period to confirm that the object-size value (the height of the horizontal line) was correct, meaning that the height of the "noise" never crossed the height of the horizontal line. At this point, following calibration, the given session was initiated. This calibration procedure produced zero false-positive video clips.

Our approach to calibration was geared toward eliminating recordings of unobservable motion (a false-positive) by decreasing the sensitivity values of the camera at the potential cost of missing small observable motion (a false-negative). In the terms of *sensitivity* and *specificity* as applied in evaluating the quality of diagnostic tests, our approach favors near-perfect specificity (i.e., 1.0; the number of true-negative recordings [no recording of unobservable motion] is equal to the number of false-positive [recording of unobservable motion] plus true-negative recordings) relative to a potential decrement in sensitivity (i.e., less than 1.0; the number of true-positive recordings [recording of observable motion] is slightly less than the number of false-negative [no recording of observable motion] plus true-positive recordings). That is, by calibrating the software and changing sensitivity to a value at which no electromagnetic "noise" was recorded, we did not allow false-positive recordings.

General procedure. For all conditions, a pre- or post-buffer was not set, the trigger-period was set at 0 s to ensure that each instance of motion was detected, history was set at 100 to increase the likelihood that each instance of motion was detected as a single motion event, and the detection window was set to 100% of the video feed. Prior to each assessment, the calibration procedure described previously was conducted and the light level in the room was recorded via the lux meter.

During each session, a researcher systematically moved a box on the metal rails into and out of the video feed in half-inch increments starting at 0.5 inches; the half-inch distances were marked up to 15 in on the table next to the metal rails as a guide in luminescent paint, which made the marked distances observable in the dark. For each movement, the researcher observed the activity monitor to determine if the movement produced an area plot with a height that crossed the threshold for the motion to be recorded (i.e., the height of the horizontal line as determined by the object-size value). If the movement did not cross the threshold, another movement was programmed at the further half-inch distance. If the movement did cross the threshold, the distance was scored (e.g., 7.5 in), and the box was moved again at the same distance to obtain a repeated measure that the camera would record the movement at this distance. Next, the researcher moved the box twice at the distance that was one half-inch less than the distance at which the movement was recorded (e.g., 7.0 in) to confirm that the movement would not be recorded. Last, the box was moved twice at the distance that it was recorded (e.g., 7.5 in) to replicate the results. This eight-trial sequence of shifting the distances above and below the distance at which the movement was recorded was akin to a reversal design. Screenshots of the box in the video feed were captured when the distance was initially determined and when the distance was replicated, and the percentage of the box relative to the video was calculated as described below. This set of procedures was conducted twice for each box size (6, 12, 24, & 32 in), which resulted in eight sessions per condition. The order of sessions was randomized prior to each condition.

Assessment 1: Does the camera detect motion based on a certain percentage of the detection window, independent of box size (exposure 50)? We assessed whether the percentage of the detection window that was comprised of movement – rather than the size of the object created movement – affected motion detection by moving four boxes that differed in size into the video until motion was recorded. Only researchers were present in the room with a laptop (which was out of the view of the camera) to move the boxes and observe the activity monitor on the laptop. There were no other objects in the room. Besides the light from the laptop, no other light was present, and the lux meter confirmed the absence of light with a reading of 0.0 lux. The value of the exposure setting on the camera was 50, its default value.

Assessment 2: How does the presence of artificial light and multiple objects affect motion detection (exposure 50)? Because we saw a decrement in the sensitivity value when no observable light was present as a result of electromagnetic “noise,” we assessed how the presence of artificial light and multiple objects affected motion detection. We hypothesized that adding artificial light and multiple objects may negatively affect motion detection because of the number of surfaces upon which light may be reflected. Evaluating these variables is important because an individual's bedroom may include a nightlight and toys or furniture in the vicinity of the bed. The position of the researchers and laptop were identical to the arrangement in Assessment 1, and the exposure value remained at 50.

Artificial light. To assess the effects of artificial light on motion detection, a Leviton 4W manual nightlight was present (the bulb was not in view of the camera).

Multiple objects. To assess the effects of multiple objects on motion detection, bedroom objects such as furniture and toys were present on the table on which the boxes were moved and in the room surrounding the table.

Artificial light and multiple objects. Artificial light and multiple objects were present to assess the effects of both variables on motion detection.

Assessment 3: How does artificial light and multiple objects affect motion detection with an exposure setting of zero (exposure 0)? As described, although the light meter reported 0.0 lux in the absence of light, the illumination from the laptop present during Assessments 1 and 2 contributed to the electromagnetic "noise." As a result, we decreased the sensitivity value during those assessments to avoid video clips with no movement (i.e., false-positive clips). The exposure setting affects the amount of electromagnetic "noise" (invisible light waves) and visible light waves that enter the camera lens (Amer & Dubois, 2005; Rabie, 2004), and can be changed to mitigate the effects of these light waves. The *exposure* setting is affected by a combination of the shutter speed, aperture, and the International Organization for Standardization (ISO) setting (Raskar, Agrawal, & Tumblin, 2006). By default, exposure is set at 50 (range, 0 to 100), and we changed the value to 0 to allow the least amount of electromagnetic and artificial light to contact the camera's image sensor[6]. We repeated the conditions in Assessment 2 to determine how artificial light and multiple objects affected motion detection under conditions in which exposure was set at the lowest value.

Dependent measures and interobserver agreement. The area of the detection window and the area of the horizontal surface of the box in the detection window was measured with an image measurement program (ImageJ©). The area of the box was measured in cm^2 by using a freehand tool to digitally trace the perimeter of it, and the area of the video feed was measured in the same manner. We divided the area of the box by the area of the detection window to determine the percentage of the video feed that the box comprised and converted the quotient to a percentage. In addition, the distance at which motion was detected was measured in inches and recorded during each session using paper and pencil.

During each assessment, we used a screen recording program to record the activity monitor on the desktop of the laptop. A secondary observer watched the recordings and scored data on the extent to which the camera detected movement for 25% of the conditions. During each assessment, the observer recorded, using paper and pencil, whether motion was detected on the four trials at the distance in which the camera detected motion and whether motion was not detected on the four trials at the half-inch

[6] There is no option to change shutter speed, aperture setting, or ISO individually, thus we cannot be sure which setting was modified when we changed the exposure setting to zero.

shorter distance in which the camera did not detect motion. The secondary observer also recorded the distance the box moved on all eight trials. The primary and secondary observers' records were compared using a trial-by-trial analysis. For each trial, an agreement was defined as both observers recording that motion was or was not detected and both observers recording the same half-inch distance the box was moved. Interobserver agreement was calculated by dividing the number of agreements by the number of agreements plus disagreements and converting the quotient to a percentage for each assessment. Mean agreement was 100% for motion and distance moved, respectively. The secondary observer also viewed screen shots of the primary observer digitally tracing the perimeter of the box and the area of the video feed and calculating the percentage of the video feed occupied by the box. An agreement was defined as the secondary observer calculating the same percentage of the video feed occupied by the box. Mean agreement was 100% across all boxes.

Results and Discussion

The organization of Figures 3, 4, and 5 that depict the results from Assessments 1, 2, and 3 are identical. The primary y-axis denotes the mean percentage (scale 0 - 9%) of the area in the detection window that was comprised by a given box across two sessions and is represented by a black bar. The secondary y-axis denotes the distance at which a given box was moved when motion was detected (scale 0 - 15 in) and is represented by a white circle. The x-axis denotes the width of each box. The level of light detected by the lux meter is denoted in each panel.

Assessment 1. The results from the assessment are depicted in Figure 3. The 32-, 24-, 12-, and 6-in boxes comprised 7.2%, 5.5%, 2.7%, and 2.2%, respectively, of the detection window when motion was detected. For the distances that the boxes had to be moved, the distance remained near 5.5 in (range, 4.5 to 6.0) despite the widths of the boxes being reduced by 63% (12-in box) and 81% (6-in box) relative to the largest box (32-in).

Prior to conducting the assessment, we hypothesized that the size of the box would not influence the camera detecting motion; instead, the percentage of the detection window with movement for motion detection, regardless of box size (and object-size), was the critical variable. Our data, by contrast, indicated that the width of the box affected the percentage of the detection window required for motion to be detected, and, interestingly, smaller boxes that comprised a *smaller* percentage of the detection window were detected as motion. That is, when smaller boxes were used, smaller percentages were obtained, and the distances required to achieve those percentages decreased with the box size. Considering the results across all box sizes, the results are noteworthy because the camera detected motion that comprised less than 10% of the detection window. Furthermore, the smallest percentage of the detection window that resulted in motion detection was obtained with the smallest box (6 in) at approximately 2.0%. The detection of small movements has important implications in terms of detecting adult and child movements that vary in size in their bed such that we may be able to predict whether motion will be detected based on the size of their limb. For example, a child's arm and hand may comprise a sufficient percentage (i.e., 2.0%) of the detection window, whereas a child's hand alone may not.

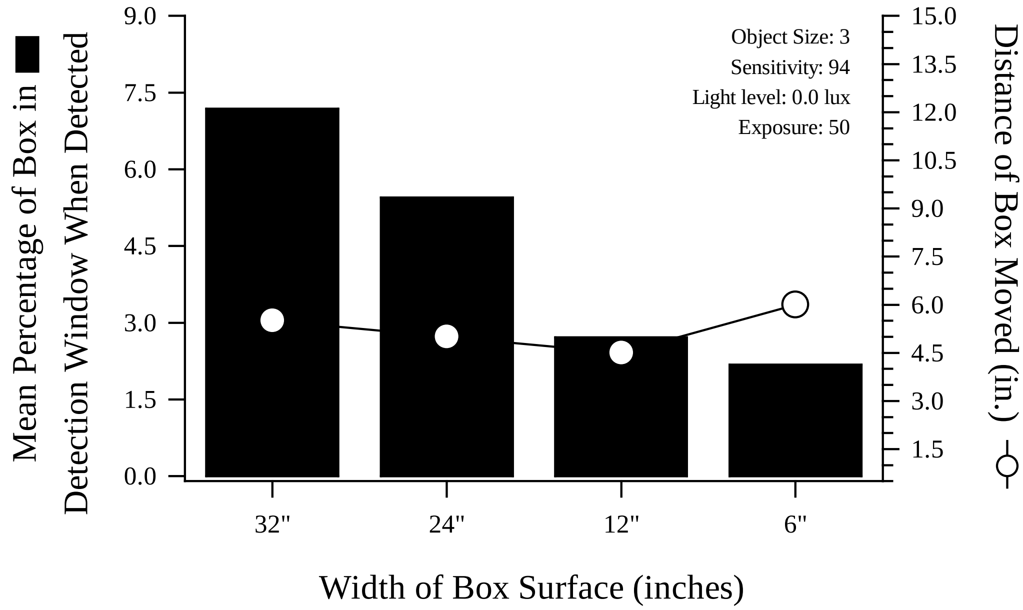

Figure 3. The results from Assessment 1. The x-axis denotes the width of the box surface. The primary y-axis indicates the mean percentage of the surface of the box in the detection window when motion was detected, denoted by the black bars. The secondary y-axis indicates the distance, in inches, the box was moved until motion was detected, denoted by the white data points. The object-size and sensitivity settings were determined from the calibration process prior to the assessment.

Assessment 2. The effects from the artificial-light, multiple-objects, and artificial-light-plus-multiple-objects conditions are depicted across the panels in Figure 4. In the first panel, following the calibration procedures with the 4W light and exposure set at 50, we obtained a sensitivity setting of 91 and a light level of 0.5 lux. Across all boxes sizes, motion was not detected at the farthest distance that the boxes could be moved into the detection window (15 in.). The results obtained when multiple objects were added, without the 4W light, are depicted in the second panel. During the calibration procedure, we obtained a sensitivity setting of 92 and a light level of 0.0 lux. The 32- and 24-in boxes were detected at 8.4% and 6.4% of the detection window, but the 12- and 6-in boxes were not detected at the farthest distance into the detection window. The third panel depicts the data obtained during the artificial-light and multiple-objects conditions. During the calibration procedure, we obtained a sensitivity setting of 89 and a light level of 0.4 lux. As we observed in the artificial-light condition, none of boxes were detected at the farthest distance.

Lower sensitivity values, 91 and 89, were observed during the calibration procedures for artificial-light and artificial-light-plus-multiple-objects conditions, respectively, compared to the sensitivity value of 94 that was observed Assessment 1. The motion-detection camera failed to detect the motion produced by all the box sizes, despite that the boxes were moved eight or more inches into the detection window relative to the distances in Assessment 1. As a result, the camera may not be acceptable to use under these conditions in practice because child and adult movements that are indicative of being awake (e.g., sitting up in bed, playing with toys) may fail to be detected. For the multiple-objects condition, the sensitivity value was 92, and only the two larger boxes were detected, and the percentage of the detection window was slightly larger than the percentages obtained in Assessment 1. Although the light level was 0.0 lux, the presence of multiple objects increased the amount of electromagnetic "noise" due to the number of objects that contrasted with background; as a consequence, a lower sensitivity value was required. The results suggest that under these conditions the camera may not detect motion produced by smaller adult and child movements such as leg and arm movements.

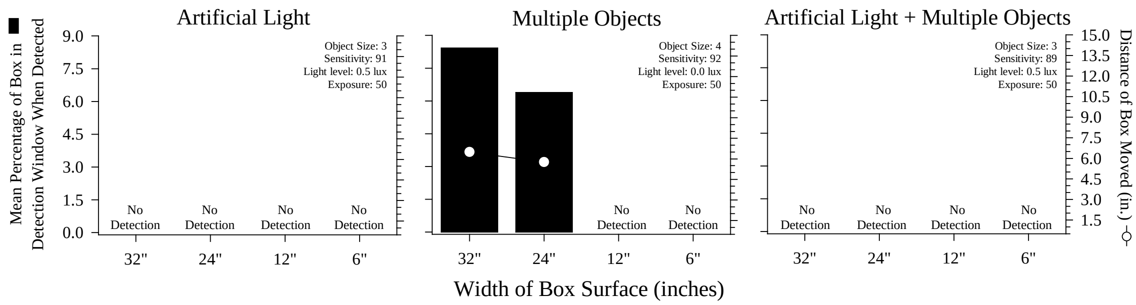

Figure 4. The results from Assessment 2. Each panel depicts data from the assessments of artificial-light, multiple-objects, and artificial-light-plus-multiple objects with 50 exposure on the motion-detection camera. The x-axis denotes the width of the box surface. The primary y-axis indicates the mean percentage of the surface of the box in the detection window when motion was detected, denoted by the black bars. The secondary y-axis indicates the distance, in inches, the box was moved until motion was detected, denoted by the white data points. The object-size and sensitivity settings were determined from the calibration process prior to the assessment.

Assessment 3. In Assessment 3, we assessed the same variables as in Assessment 2, but with the exposure value set at zero. In the artificial-light condition (first panel, Figure 5), we obtained a sensitivity value of 97 and a light level of 0.5 lux. The 32-, 24-, and 12-in boxes were detected when they comprised 7.1%, 5.2%, and 3.0% of the detection window, respectively, and these percentages are nearly identical to those obtained in Assessment 1. However, the 6-in box was not detected at the farthest distance into the detection window. In the multiple-objects condition (second panel), we obtained a sensitivity value of 94 and a light level of 0.0 lux. As in the artificial-light condition, the 32-, 24-, and 12-in boxes were detected at 7.8%, 5.2%, and 4.1% of the detection window, respectively, and the 6-in box was not detected. In the artificial-light-plus-multiple-objects condition, we obtained a sensitivity value of 93 and a light level of 0.5 lux, and the 32- and 24-in boxes were detected at 8.7% and 7.3% of the detection window, respectively. The 12- and 6-in boxes were not detected at the farthest distance into the detection window.

By changing the exposure setting to zero in Assessment 3, the amount of light that entered the camera was reduced, and, as a result, the sensitivity values following calibration were higher in each condition in comparison to Assessment 2. The 32- and 24-in boxes were detected across all conditions and the 12-in box was detected in two of three conditions; the percentages of the detection window required for motion to be detected were similar to those obtained in Assessment 1. Moreover, in the artificial-light condition, the 12-in box was detected when it comprised only 3.0% of the detection window. These outcomes indicated that by changing the exposure to zero, the negative effects of artificial light and multiple objects, as observed in Assessment 2, can be mitigated. In the absence of the nightlight and furniture in Assessment 1, we observed that motion from the smallest box could be detected when it comprised as little as 2.0% of the detection window, which may translate to capturing human limb movements in an applied setting. In addition, the calibration procedure we developed allowed us to avoid the camera recording video clips with unobservable motion. As important, we learned from Assessment 2 that the presence of artificial light and furniture increases the amount of electromagnetic noise and, as a consequence, the precision of motion detection is negatively affected due to the low sensitivity settings on the camera. However, in Assessment 3, we showed that changing the exposure value to zero notably limits the amount of light that enters the camera, which mitigates the problem introduced by artificial light and furniture.

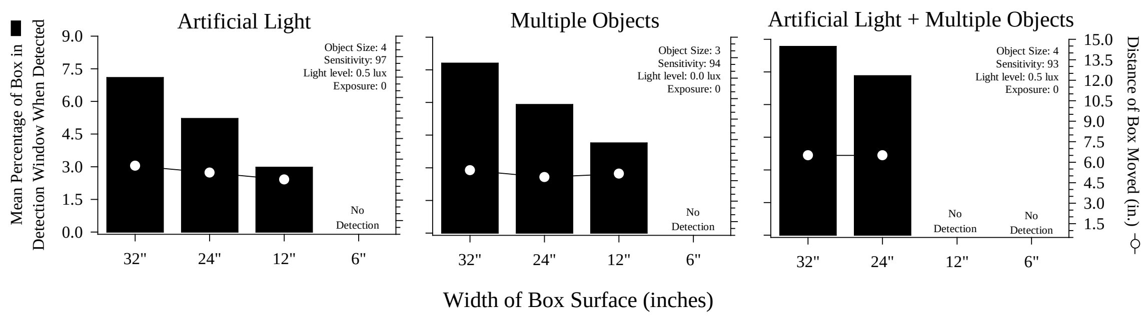

Figure 5. The results from Assessment 3. Each panel depicts data from the assessments of artificial-light, multiple-objects, and artificial-light-plus-multiple objects with zero exposure on the motion-detection camera. The x-axis denotes the width of the box surface. The primary y-axis indicates the mean percentage of the surface of the box in the detection window when motion was detected, denoted by the black bars. The secondary y-axis indicates the distance, in inches, the box was moved until motion was detected, denoted by the white data points. The object-size and sensitivity settings were determined from the calibration process prior to the assessment.

The applied implication of the precision of the motion-detection camera depends on the generality of these results to human motor movements. Research on whether limb movements that comprise approximately 2.0% to 3.0% or more of the detection window will be recorded should be conducted. The results from such an evaluation would allow us to predict which movements will be captured by the camera.

Study 2

The purpose of Study 2 was to determine the extent to which common human motor movements could be detected with the infrared motion-detection camera. We programmed a variety of motor movements that may be exhibited by humans in bed.

Method

Camera setup, motion-detection settings, and setting. The same camera and infrared illuminator, and the position of the equipment in Study 2 matched Study 1. We learned from Study 1 that the exposure setting determines how artificial light and multiple objects affect the influence of electromagnetic “noise” on motion detection. For this reason, we set the exposure setting value to zero throughout this study to minimize the negative effects of electromagnetic “noise.”

One Black adult and one Caucasian adult participated in this study. We chose to include a Black and Caucasian adult to determine whether there were any differences with regard to motion detection across skin complexions. The study was conducted in the same room as in Study 1 with no artificial light or multiple objects present. The room was barren, and only one adult and the researcher were present during each session.

Motor movements. We selected motor movements that varied in size. *No movement (control)* required no change in position from the adult (i.e., the adult lay still in a supine position during the interval). *Mouth movement* required continuous movement of the mouth to emit the word, “Mommy” without vocal production for 3 s. *Hand flip* was defined as the continuous movement of turning the hand from a downward position, 180º to one side and back. *Lower arm* was defined as bending the arm, from the elbow down, up 90º and back down. *Whole arm* was defined as movement of the entire arm from the down position upright (perpendicular) and back to the initial position. *Leg bend* was defined as movement of the leg, from the knee and below, straight toward the chest and back to the initial position for 3 s. *Whole leg* was defined as movement of the entire leg from a straight position, upward, and back to the initial position for 3 s. *Sit up* was defined as moving from the supine position to an upright position for 3 s. *Turn body* was defined as continuous movement of the entire body from the supine position to one side and back for 3 s.

General procedure. We generated a single script with the eight pre-defined movements randomly programmed to occur on five separate occasions (see Figure 6). The movements were programmed at 20-s intervals and the duration of each movement was 3 s (e.g., seconds 20 to 23, 40 to 43, 60 to 63, etc.). To increase the procedural integrity with which the adult engaged in programmed movements, the lead author created an audio recording that cued the timing and type of movement at each interval. The adult wore ear buds and listened to the script on an Apple Ipod 4th generation Voice Memo program. The researcher dictated the topography of the upcoming movement 1.5 s before each 20 s interval (e.g., seconds 18.5, 38.5, 58.5, etc.) to ensure the movement occurred at each 20-s interval. Five intervals in which no movement occurred were programmed to serve as a control by testing whether the camera did not produce a video clip when no movement was programmed. Each evaluation comprised 45 intervals with movement across 15 min.

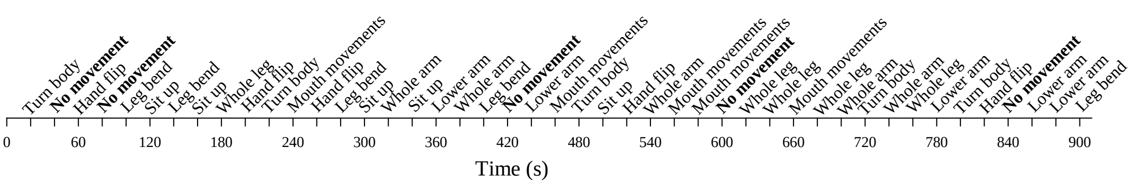

Figure 6. The schematic shows the distribution of programmed movements throughout the session. The intervals during which no movement (control) was programmed are depicted in boldface type.

Assessment 1: Which human movements would the camera reliably detect with the size of the detection window set at 100% of the video feed? The condition was conducted with a detection window that was 100% of the video feed. Screenshots of the view from the video camera are shown in the top and bottom panels of Figure 7 for the Caucasian and Black adult, respectively. Prior to each session, we conducted the calibration procedure as described in Study 1.

Assessment 2 (refining the camera's precision): Would decreasing the size of the detection window until a target movement comprised at least 2.0% predict the reliable detection of this movement? The results from Assessment 1 in Study 1 suggested that the motion of a small (6-in) object that comprised at least 2.0% of the detection window could be detected. We modified the size of the detection window such that the smallest movement that was not detected in the 100%-Detection-Window condition (Assessment 1) comprised 2.0% of the detection window. By changing the size of the detection window, relative to the video feed, the percentage of the detection window for which different body parts comprised decreased. Prior to each session, we ensured that the target movement comprised approximately 2.0% of the detection window by digitally tracing the perimeter the movement (i.e., body part) and the area of the detection window. We divided the area of the target movement by the area of the detection window and converted the quotient to a percentage.

Size-manipulation 1. We decreased the size of the detection window such that the largest movement that was not detected in Assessment 1 comprised $\geq$ 2.0% of the detection window for both adults (middle column, Figure 7).

Size-manipulation 2. Based on the movements not detected at the previous detection-window size, we further decreased the size of the detection window such that the percentage of the next largest movement comprised $\geq$ 2.0% of the detection window for both adults (right column, Figure 7). For the Caucasian adult, we decreased the detection window to a smaller percentage of the video feed, but the next largest movement did not comprise 2.0% of the detection window. We did not decrease the size of the window further because previously detected movements (e.g., leg bend) may not be detected as the detection window would not have encompassed the entire limb. In other words, the conditions under which leg bend, whole leg, sit up, and turn body were detected would have changed which could have affected whether the camera detected those movements if the entire limb was not within the detection window.

Design. We used a changing-criterion design (Hartmann & Hall, 1976) to demonstrate that 2.0% predicted the detection of target movements for the Black adult.

Dependent measures, interobserver agreement, and procedural integrity. The occurrence of a programmed movement during an interval represented one opportunity during which the primary observer scored (a) the topography of the movement and time at which it occurred and (b) whether a video clip was produced by the motion-detection camera. The percentage of opportunities that motion was detected for each programmed movement and the no-movement (control) intervals were depicted graphically. The percentage of the detection window comprised by each targeted movement was measured prior to each session. The measure was calculated by digitally tracing the perimeter of each programmed movement and the area of the detection window, and then dividing the area of the programmed movement by the area of the detection window and converting the quotient to a percentage.

We obtained interobserver agreement from a second independent observer that scored whether the programmed movements were detected by the camera for 33% of sessions. The observer was provided with the recorded video of the session and the video clips produced by the camera during the session. Each video clip was reviewed and the topography of the movement and timestamp at which it occurred was scored, and the secondary observer’s data were compared to the primary observer’s data on an interval-by-interval basis. Agreement was defined as both observers scoring the same topography of movement in the video clip or both scoring no video clip. Interobserver agreement was calculated by dividing the number of agreements by the number of agreements plus disagreements and converting the quotient to a percentage for each session. Mean agreement across all sessions was 100%.

We obtained procedural integrity data for 33% of sessions by comparing a primary and secondary observer's records of which movements occurred on an interval-by-interval basis from the recorded video of a session. For each 20-s interval, a correct movement was defined as the adult's movement matching the programmed movement, and an incorrect movement was defined as the adult's movement differing from the programmed movement. The number of correct movements was divided by the number of correct plus incorrect movements and converting the quotient to percentage. Procedural integrity was 100%.

Results and Discussion

The topographies of programmed movements are denoted on the y-axes in Figure 8 and are listed in ascending order from the largest movement to no movement for the Caucasian (top row) and Black (bottom row) adults. The percentage of opportunities in which the programmed movements were detected is denoted on the x-axes. The gray area plot indicates which movements would be predicted to be detected based on the 2.0% criterion for motion detection; percentages $\geq$ 2.0% are in boldface font.

With the detection window set at 100% of the video feed (Assessment 1, left column), turn body, sit up, whole leg, and leg bend were detected for 100% of the programmed instances for both adults. These findings support the reliability of the camera to detect the same movement across repeated opportunities. In addition, the camera reliably detected movements that comprised less than 1% of the detection window across both adults (leg bend, 0.80 & 0.75). During Assessment 1 in Study 1, movement as small as 2.0% of the detection window was detected. In the current study, the exposure value was zero (based on what we learned from Study 1) instead of 50, which allowed for a sensitivity value of 97 to be obtained compared to 94 in Study 1, respectively. This may be the reason why movements smaller than 2.0% were detected.

Because whole arm was the next largest movement not detected for both adults, we decreased the detection window to a size in which the whole arm comprised approximately 2.0% of the detection window (see yellow-dotted outlines on arm in middle column, Figure 7); at this size, the detection window was 29% and 28% of the video feed for the Caucasian and Black adults, respectively (see white rectangles in middle column, Figure 7). Following this modification (Assessment 2, Size-manipulation 1), 100% of the programmed instances of whole-arm movements were detected (middle column, Figure 8). In addition, we replicated the reliable detection of all of the movements (i.e., leg bend and larger) that were detected when the window size was 100% of the video feed. For the Caucasian adult, the camera also detected 100% of lower-arm movements (1.0% of the detection window) and 60% of hand-flip movements (0.44% of the detection window). In Assessment 2 (Size-manipulation 2), the detection window was decreased to a size in which the lower arm comprised 2.0% of the detection window for the Black adult. At this size, the detection window was 16% of the video feed (right column, Figure 7). For the Caucasian adult, the detection window was decreased to a size in which hand flip was 0.90% of the detection window. As noted in the method section, we did not further decrease the size of the detection window because previously detected movements may not have been detected. At this size, the detection window was 15% of the video feed (right column, Figure 7). All movements for both adults, except mouth movements, were detected on 100% of the occurrences.

All movements that comprised 2.0% or more of the detection window were detected by the motion-detection camera every time they were programmed, which included 125 opportunities across the three conditions and both adults. Also, no video clips were produced during the programmed control intervals with no movement (or any other seconds during which a movement was not programmed). These results (a) establish the generality of the outcomes obtained with boxes in Study 1 to human movements, (b) support the reliability of the motion-detection camera to detect repeated occurrences of the same movement, and (c) suggest that skin pigment has negligible influence on the precision of motion detection. As important, by decreasing the size of the detection window to detect smaller, missed movements (Size-manipulations 1 & 2), the predicted target movements were detected in 100% of the opportunities (whole arm and lower arm). In other words, by systematically manipulating the size of detection window based on the 2.0% criterion, we showed that it was conservatively predictive of which movements would be detected.

This analog evaluation was conducted to determine how to set the size of detection window to detect small human movements prior to assessing the accuracy of the motion-detection camera to measure sleep disturbance in an applied setting. In a child's room, for example, there will likely be a balance between decreasing the size of detection window until a child's small limb (e.g., a hand) comprises 2.0% while maintaining a size large enough to record movements if the child shifts position in the bed throughout the night. As can be seen most dramatically in the screenshots from the Size-manipulation 2 in Figure 7, the bottom of the adults' feet were outside of the detection window and if the adult were to move a limb outside of the detection window, the camera would not have recorded those movements. Given that the applied objective is to capture all movements that represent awake behavior throughout the night, matching the size of detection window to the perimeter of the bed may be a good approach, but the smallest movement of interest may not equal the 2.0% criterion.

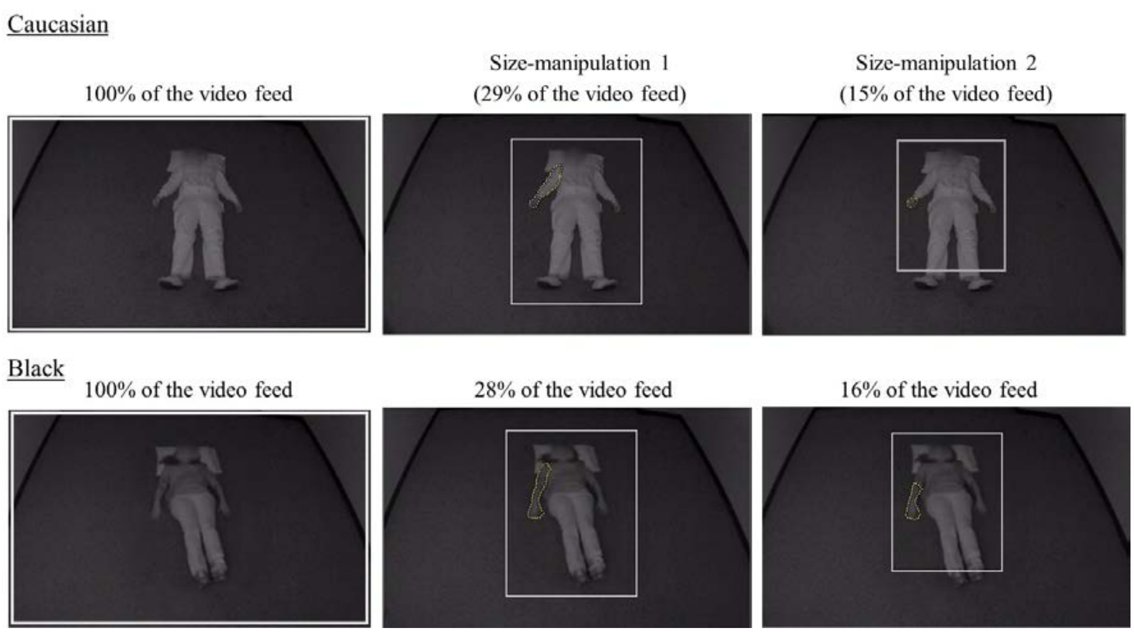

Figure 7. Screenshots of the entire video feed for each detection-window condition, by column, for each evaluation by row. The gray rectangle around each adult depicts the detection window. The body part that the detection-window size was based on is outlined in yellow.

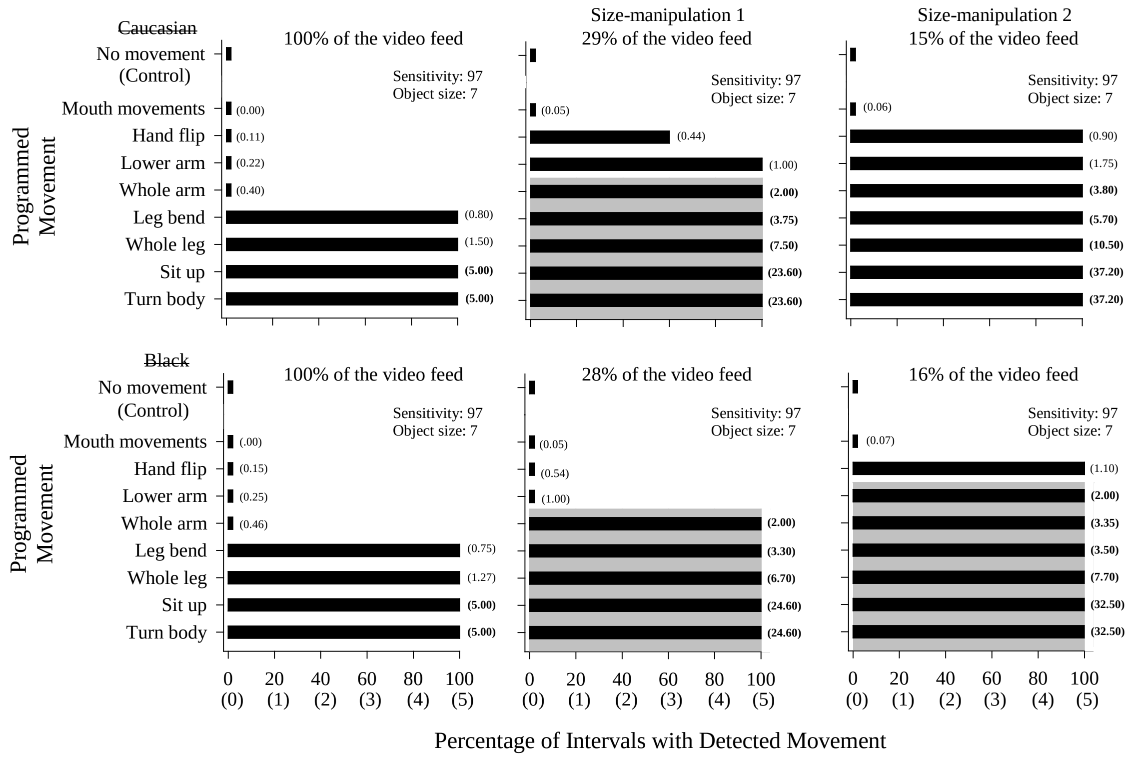

Figure 8. These graphs depict the results for the motor movement evaluation across different detection window sizes on each panel according to skin complexion. The y-axes denote the programmed movement and the x-axes denote the percent of detected movements. The secondary x-axes denote the number of movements detected. The gray area plots indicate the smallest undetected movement from the preceding evaluation, and indicate the target limb to meet 2.0% of the detection window. The values in parentheses, adjacent to the black bars, represent the percentage of the movement to the detection window; percentages ≥ 2.0% are in boldface font.

Although we evaluated a particular camera, the methods of Assessment 1 and 2 could be used to empirically derive the reliability and precision of other cameras and future versions as technological advances are achieved. The methods used in this study were not specific to the camera or software that we used in the study; rather, the motion-detection settings are common across other motion-detection cameras and software programs.

Based on the results from Studies 1 and 2, motion detection may be a viable measurement system used to measure sleep disturbance for young children in their bed. The extent to which these results are predictive of those obtained in children's bedrooms should be evaluated because it is unknown whether the precision of the camera will be affected by (a) the presence of items of various colors and sizes such as a child's comforter, blanket, pajamas, stuffed animals and (b) a blanket covering the child's limbs and body. The accuracy and time to score sleep disturbances via the motion-detection camera should be compared to other empirically supported measurement systems. One such measurement system is actigraphy. In addition to the American Academy of Sleep Medicine recommending actigraphy to determine sleep patterns and an individual's response to treatment, the ratio of studies published with actigraphy data relative to studies published with polysomnography was 1:10 in 1991 and 1:4 in 2009, which suggests that actigraphy is becoming more common in sleep research (Sadeh, 2011). Sleep diaries often supplement actigraphy output to identify periods when the actigraph is removed and to verify periods of sleep (Meltzer, Montgomery-Downs, Insana, & Walsh, 2012). MTS has been used to measure sleep (e.g., Bliwise, Bevier, Edgar, & Dement, 1990; Jin, Hanley, Beaulieu, 2013; Piazza & Fisher, 1991), but observation intervals have not been consistent across investigations. Although some of these measurement systems have been used across decades of research, we found no comparative data to determine which measurement system can be used to obtain accurate measures within a reasonable amount of time for nightly or bi-nightly data collection.

Study 3

The results from Study 2 confirmed that adult human movements 2.0% or larger are reliably detected in an analog format. The purpose of Study 3 was to measure children's sleep disturbance with the motion-detection camera and other measurement systems with empirical support to determine the accuracy of each system compared to sleep disturbance measured by a continuous (second-by-second) measurement system (criterion record), time to score sleep disturbance, and social acceptability of measurement systems. We were interested in measuring observable sleep disturbance that is incompatible with sleep for which caregivers request clinical services (e.g., a child remaining awake for extended periods during the night) rather than physiological measures of sleep.

Method

Participants and night selection. Three children diagnosed with an ASD and their parents participated in this study. We recruited participants by posting flyers in a university-based clinic and local agencies that provide resources for families with a child diagnosed with an ASD. The parent of each participant indicated that the primary sleep disturbance was sleep onset latency. Anne was a 3.5-year-old female, John was a 3.1-year-old male, and Max was a 4.5-year-old male. Each child was enrolled in a separate project on the assessment and treatment of their sleep disturbance, and, for this project, data were collected using sleep diaries, completed by the child's parents, and MTS 10 min, completed by researchers. These measurement systems were used because of their precedence in empirical investigations and because we were interested in obtaining direct-observation measures of sleep disturbance (e.g., Jin, Hanley, & Haskell, 2013; Minde, Popiel, Leos, Falkner, Parker & Handley-Derry, 1993).

Measurement systems were compared across four nights for two children and three nights for a third child, totaling 11 nights. We selected nights that included at least 30 min of total sleep disturbance was recorded using MTS with all measurement systems in place (e.g., sleep diaries were not always submitted on a daily basis or the camera may have been inadvertently turned off). Only nights during which the primary referring sleep disturbance comprised 50% or more of total sleep disturbance were eligible; that is, if total sleep disturbance was 1 hr, sleep onset latency comprised at least 30 min. Based on the durations of total sleep disturbance, the four (or three) nights for each child that were above and nearest to the 75th percentile were selected. We chose nights during baseline with elevated levels of sleep disturbance to allow the opportunity to assess whether the measurement systems would underestimate sleep disturbance. Although we selected nights to include based on a MTS 10-min measurement system, all nights were rescored using a continuous (second-by-second) video measurement system. Data on total sleep disturbance, sleep onset latency, and wakings after sleep onset from continuous measurement system for each participant are depicted in Figure 9; black, white, and gray circles denote the individual, nightly values for Anne, John, and Max, respectively. The sleep disturbance we analyzed for Anne was notably lower than John and Max because she remained outside of her bedroom for a majority of the sleep onset latency, which was excluded from our analysis because it was not captured on video. The mean total sleep disturbance (open bar) across participants was 105 min (range, 33 to 215 min); the horizontal dashed black line denotes the 30-min inclusion criterion. The mean sleep onset latency across participants was 74 min (range, 22 to 193 min). The mean wakings after sleep onset across participants was 31 min (range, 10 to 81 min).

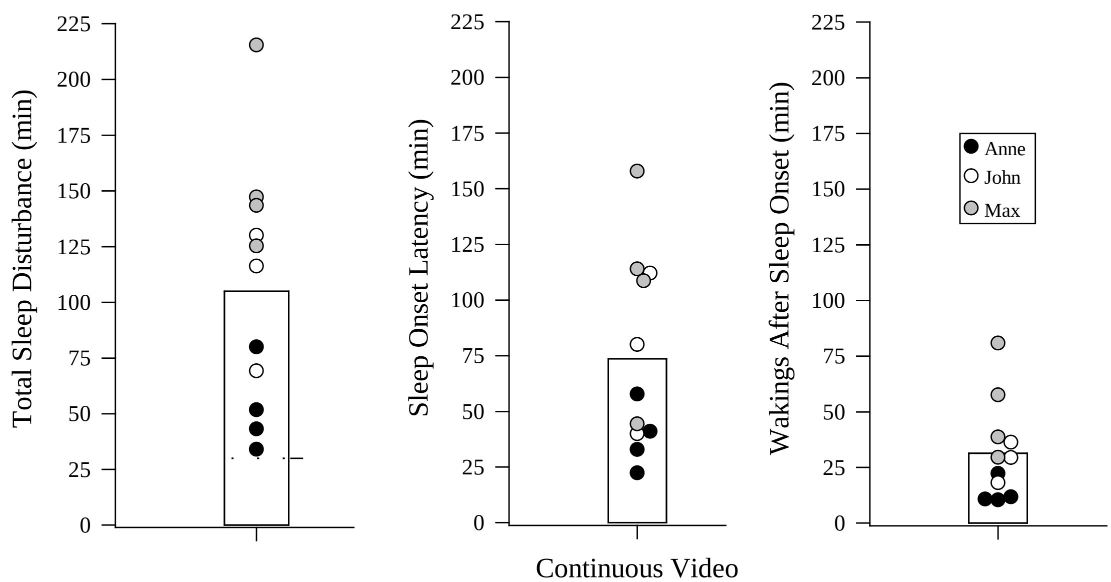

Figure 9. The y-axis depicts total sleep disturbance, sleep onset latency, and wakings after sleep onset in minutes for all participants in the first, second, and third panel, respectively. The x-axis denotes the use of the second-by-second continuous (second-by-second) measurement system to obtain these data. The white bars represent the means and the individual data points depict the value for each night for each child. The data points are color-coded by participant. The black data points denote values for Anne, white data points denote values for John, and gray data points denote values for Max. The horizontal dashed black line in the first panel depicts the 30 min criterion for inclusion in the study.

Technology setup in children's homes. Each measurement system was remote in the fact that no face-to-face contact between the researchers and the family was necessary. Prior to the study, a nighttime infrared video camera, infrared illuminator, and laptop computer (i.e., the same equipment from Study 1 and 2) were installed in each child's bedroom (see Figure 10). Letters denote features of the technology setup. The nighttime infrared video camera was positioned above the child's bed on a shelf, perpendicular to the bed *(a)*. The lens angle and infrared illuminator *(b)* was setup identical to the arrangement in Study 1. The laptop computer *(c)* was positioned on the same shelf as the camera and connected to the family's high-speed internet via an encrypted, Wi-Fi protected access 2 (WPA2), wireless connection. A VPN tunnel was established between the laptop and a desktop computer at a university-based clinic. Logmein Central, a remote assistance program, was installed on the laptop and was accessible from the desktop computer at the clinic. For all direct-observation measurement systems, the videos were remotely transferred daily from the child's home to the university-based clinic. The camera was scheduled to record automatically between the child's scheduled bedtime and wake time.

Figure 10. An image of a bedroom for one child. The setup of the (a) nighttime infrared video camera, (b) infrared illuminator, and (c) laptop computer are shown in the top-right corner of the image.

Parents were given an actigraph (Micro Motionlogger Sleep Watch, Ambulatory Monitoring Inc., Ardsley, NY), and they were asked to assist in transferring the data to the university-based clinic. We created a task analysis with images to denote each step of the process for the parents. The steps included positioning an infrared receiver that was connected to the laptop in front of the actigraph and pressing the mode button two times. Actigraphy data were transferred to the desktop computer at the clinic using the VPN tunnel.

General procedure. We met with each family prior to the study to determine the target bedtimes and wake times for each child. We determined the appropriate times based on parent preference, the Sleep Assessment and Treatment Tool (Jin, Hanley, & Beaulieu, 2013), and developmental normative data.

Measurement systems. We compared three direct-observation measurement systems and actigraphy to a criterion record. With the exception of the motion-detection camera, these measurement systems have been used in empirical investigations. Each measurement system was used to score sleep disturbance for all 11 nights. The measurement systems were applied 30 min prior to the target bedtime until the target wake time or until child left the bedroom if the child awoke after the target wake time to ensure that all nighttime sleep was captured. In the event that a child came in the room after their target bedtime or left the room during the night, we used sleep diaries to determine whether the child was awake.

Criterion record: Continuous video (second-by-second). The motion-detection camera simultaneously recorded continuous video and motion-detection video. The continuous-video function was used to record continuously throughout the night and create a criterion record. A criterion record of sleep disturbance was obtained by scoring awake and sleep on a second-by-second basis for each night. Videos were viewed on a

17 in external monitor using GOM media player, and all data were entered into a Microsoft Excel spreadsheet shown on a 14 in laptop monitor. The spreadsheet was pre-filled with the time in one column and the topography of awake behavior (see operational definitions) was scored in an adjacent column. The observer paused and rewound the video as needed.

Motion detection. In addition to the continuous-recording function, the motion-detection camera was programmed to detect motion throughout the night. The software was calibrated in the child's bedroom and the detection window was arranged such that the child's lower arm comprised 2.0% of the detection window, which was informed by the results in Studies 1 and 2. Data collection was identical to the procedures described for the continuous measurement system.

MTS 5 min and MTS 10 min. We used paper and pencil to score the continuous video by observing for a maximum of one min every 5 or 10 min throughout the night after the child initiated sleep. To measure sleep onset, we viewed the video continuously from the target bedtime until the child met the definition of awake and then proceeded to the next 5- or 10-min interval from the target bedtime (e.g., if the target bedtime was 8:00:00 pm and the child was awake at 8:02:37 pm, the next interval would begin at 8:05:00 pm or 8:10:00 pm). Observations continued during each subsequent 5- or 10-min interval until the target wake time or until the child awoke, if sleep continued past the target wake time. A partial-interval recording system was used for each 5- or 10-min interval in that we observed for a maximum of one min during each interval to determine whether the child was awake. If the child met the definition of awake, the data collector recorded awake and the topography and the moved to the next interval.

***Actigraphy*.** The actigraph was placed on the child's nondominant wrist 30 min prior to the target bedtime and recorded activity throughout the night. We asked parents to depress the event button to denote the time at which the bid goodnight occurred and again at the time at which the child was removed from the bedroom in the morning.

Dependent measures. *Total sleep disturbance* was defined as the duration, in min, the child was awake from the target bedtime until the target wake time or until the child awoke, if sleep occurred beyond the designated wake time. *Sleep onset latency* was defined as the duration, in min, the child was awake from the target bedtime until 10 consecutive min without the child meeting the definition of awake. For the continuous video and MTS 5 and MTS 10 min measurement systems, sleep onset occurred when 10 consecutive min elapsed without the child meeting the definition of awake from the target bedtime. For MTS 5 and MTS 10 min, if the child was awake at any time while watching for 10 consecutive min, observers advanced 5 or 10 min from the target bedtime, respectively. For motion detection, sleep onset occurred when no video clips were produced for 10 consecutive min. For actigraphy, we used the algorithm created by Sadeh, Sharkey, and Carskadon (1994) to identify when the child initiated sleep. The algorithm was applied to the activity recorded throughout the night using Action-W software (this software was included with the actigraph).

Wakings After Sleep Onset was defined as the amount of time, in minutes, the child met the definition of awake, after sleep onset was initiated. For the continuous and motion detection measurement systems, all seconds that the child was awake were summed and divided by 60 to convert the measure to min. For MTS 5 and MTS 10 min, the number of intervals during which the child was awake, after sleep onset, was multiplied by 5 or 10 min. For actigraphy, we used the pre-determined algorithm to calculate the number of min the child was awake after sleep onset.

Time to Score Sleep (i.e., efficiency) measures, in hr, were obtained from the time when scoring began to the time at which scoring was complete. Data were not collected on the time required for data analysis (e.g., time to add the seconds of awake to determine the amount of wakings after sleep onset). For direct-observation measurement systems, we began timing from the target bedtime and continued until the target wake time or until the child awoke, if sleep continued past the target wake time.

Direct-observation operational definitions. We did not use a binary measurement system to score whether the child was awake or asleep. When the child met the definition of awake, we obtained qualitative information pertaining to what the child was doing when awake. We obtained these qualitative data because they can be linked to developing individualized treatments to address competing activities or undesirable sleep dependencies at bedtime and throughout the night. Children were scored as *awake* if they (a) engaged in physical movement that met a 10-s onset criterion (Emde & Meltcalf, 1970; Sforza, Zamagni, Petiav, & Krieger, 1999), were sitting up (no contact between the bed surface and the child's head and back), were standing up, or had their eyes open (Jin, Hanley, & Beaulieu, 2013), (b) emitted vocalizations such as laughing, talking, singing, crying, calling out, or making requests with the exception of sneezing, coughing, or yawning (Jin, Hanley, & Beaulieu, 2013) and snoring, (c) actively manipulated of toys, stuffed animals, or bedding materials for 5 s (Jin, Hanley, & Beaulieu, 2013), and (d) engaged in motor stereotypy such as body rocking or repeatedly flapping any object for 5 s (Hanley, Iwata, Thompson, & Lindberg, 2000; Jin, Hanley, & Beaulieu, 2013). Any behavior that did not meet the definition of awake was defined as *sleep*. For physical movement and object manipulation and stereotypy, data collectors used 10-s and 5-s offset criterions, respectively.

Interobserver agreement. For measures on sleep disturbance, a second observer scored at least 25% of nights for Anne and Max using all measurement systems, and 33% of nights for John. Interobserver agreement for the continuous and motion-detection measurement systems was calculated using a time-window analysis (MacLean, Tapp, & Johnson, 1985; Mudford, Martin, Hui, & Taylor, 2009). For sleep onset and wakings after sleep onset, agreement was scored if the secondary observer reported the same values for sleep onset and waking after sleep onset within ± 2 min of the primary data collector's times. For specific categories of awake, an agreement was scored if the secondary observer recorded the same category within ± 3 s of the primary data collector's timestamp. For all three children, mean agreement for total sleep disturbance using the second-by-second continuous measurement system was 99% (range, 98% to 99%). For the motion-detection measurement system, mean agreement for sleep onset and wakings after sleep onset was 100% for all three children. For MTS 5- and 10-min, interval-by-interval agreement was calculated. An agreement was defined as an interval in which both observers recorded the child as awake. Agreement was calculated by dividing the number of intervals of agreement by the total number of intervals throughout the night. For MTS 5 min, mean agreement for sleep onset was 95% (range 92% to 100%) and 96% (range 95% to 97%) for wakings after sleep onset. For MTS 10 min, mean agreement for sleep onset was 100% and 93% (range 85% to 100%) for wakings after sleep onset. Mean agreement for actigraphy was calculated by comparing the value each observer obtained from the actigraphy software. Agreements were defined as the secondary observer reporting the same values for sleep onset latency and waking after sleep onset within ± 2 min of the primary data collector's time. Agreement coefficients were binary; if the values were the same, the agreement was 100%, and if the values differed, agreement was 0%. Mean agreement was 100% for sleep onset and wakings after sleep onset, respectively.

For the efficiency measures, a second observer recorded the time to score each night for 27% of the nights for each measurement system from screenshots of a stopwatch program on the primary observer's computer. We compared the value each observer obtained from the screenshots to determine an agreement coefficient. Agreements were defined as the secondary observer reporting the same value for the time to score each night within ± 2 min of the primary data collector's time. Agreement coefficients were binary; if the values were the same, agreement was 100%, and if the values differed, agreement was 0%. Agreement for all measurement systems was 100%.

Social validity of measurement systems. After the treatment evaluation was completed (data not reported in this article), we asked the parents to rate and rank the acceptability of the measurement systems. The parents of Anne and Max rated the measurement systems using a 7-point Likert scale (7 = strongly agree, 4 = no opinion, 1= strongly disagree).

Results and Discussion

To what extent did the accuracy of the motion-detection camera compare to a continuous (second-by-second) measurement system?

The first column of the first panel of Figure 11 depicts accuracy measures for motion detection for total sleep disturbance. The x-axis denotes the measurement system and the y-axis depicts the minutes of error for total sleep disturbance compared to total sleep disturbance from the continuous (second-by-second) measurement system. If the duration of total sleep disturbance differed, we calculated the arithmetic difference by subtracting the lower duration from the higher duration to calculate the error (difference). A positive value indicates overestimation and a negative value indicates underestimation relative to the continuous measurement system. The white bar represents the mean of the 11 nights and the data points indicate individual nights for each child. The errors from the continuous measurement system show a mean underestimation of -23 min (range, -10 to -44 min).

Given that we observed errors of underestimation, we analyzed the error for sleep onset latency and wakings after sleep onset to determine whether the error was a result of inaccurate measures obtained during different portions of the night; these data are shown in the first columns of the second and third panels of Figure 11, respectively. For sleep onset latency, motion detection yielded a mean error of -4 (range, -11 to 0 min). In other words, the motion-detection measurement system indicated that the child initiated sleep at similar times as obtained with continuous measurement system. For wakings after sleep onset, we observed systematic underestimation for motion detection with a mean of -20 min (range, -36 to -10 min).

We speculate that the size of the detection window, relative to the video feed, and that behavior that did not require movement (e.g., vocalizations) was scored as awake from the continuous measurement system, affected underestimation errors for the motion-detection measurement system. If the child moved outside of the detection window during the night, any sleep disturbance that occurred would not be captured. In other words, if the child was awake, but not in the detection window, the child was scored as asleep because no video clips were produced. We used each of these measurement systems in isolation, such that if we observed the child move outside of the detection window during a video clip, we did not use the continuous measurement system to observe the child. The child may have been outside the detection window because it was small enough so that the lower arm was 2.0% of the detection window. Thus, it was smaller than the size of the bed.

To determine the duration each child was within the detection window, we reviewed each night and tallied the seconds at which the child's entire body was within the detection window. This analysis makes the results comparable to the analyses in Studies 1 and 2. No child was entirely within the detection window more than 20 min and the least amount of time a child was within the detection window was just over 1 min. That is, these children were entirely within the detection window for less than 3% of the night across all nights. To determine the accuracy of motion detection under the conditions in which we calibrated the software (i.e., the child was entirely within the detection window), we compared the seconds the child was within the detection window *and* scored as awake from the criterion record to the data obtained with motion detection during the same seconds. The data from this comparison are depicted in Figure 12. The y-axis depicts the percentage of seconds in which there was agreement and disagreement using motion detection for sleep disturbance compared to continuous video, and the x-axis denotes nights for each child. The vertical lines represent the percentage agreement of the occurrence of sleep disturbance with a mean of 76% (for right-most vertical line), and the white and gray stacked bars depict the type of disagreement in the form of subtle movements (i.e., movements that were approximately 2.0% or less of the detection window) and eyes open, respectively. On some nights, there was no disagreement (night 1 for John and night 3 for Anne); on other nights, disagreement was as low as 54% (night 2 for Anne). The type of disagreement for John was comprised of subtle movements and eyes open. For Anne, disagreement was only due to subtle movement. For Max, most of the disagreement was a result of his eyes open (i.e., quiet wakefulness) without movement. These disagreement data are consistent with our conclusions from Studies 1 and 2 that movements 2.0% or less would not be captured. Also, these data indicated that the motion-detection camera was calibrated correctly because when a movement was 2.0% or greater, it was detected which resulted in almost 80% agreement. For this reason, researchers should evaluate whether adding multiple detection windows that span the entire video feed, set at the 2.0% criterion, would capture movement regardless of the child's location in the bedroom. We did not initiate this analysis to ensure that the methods of this study aligned with the methods described for Studies 1 and 2.

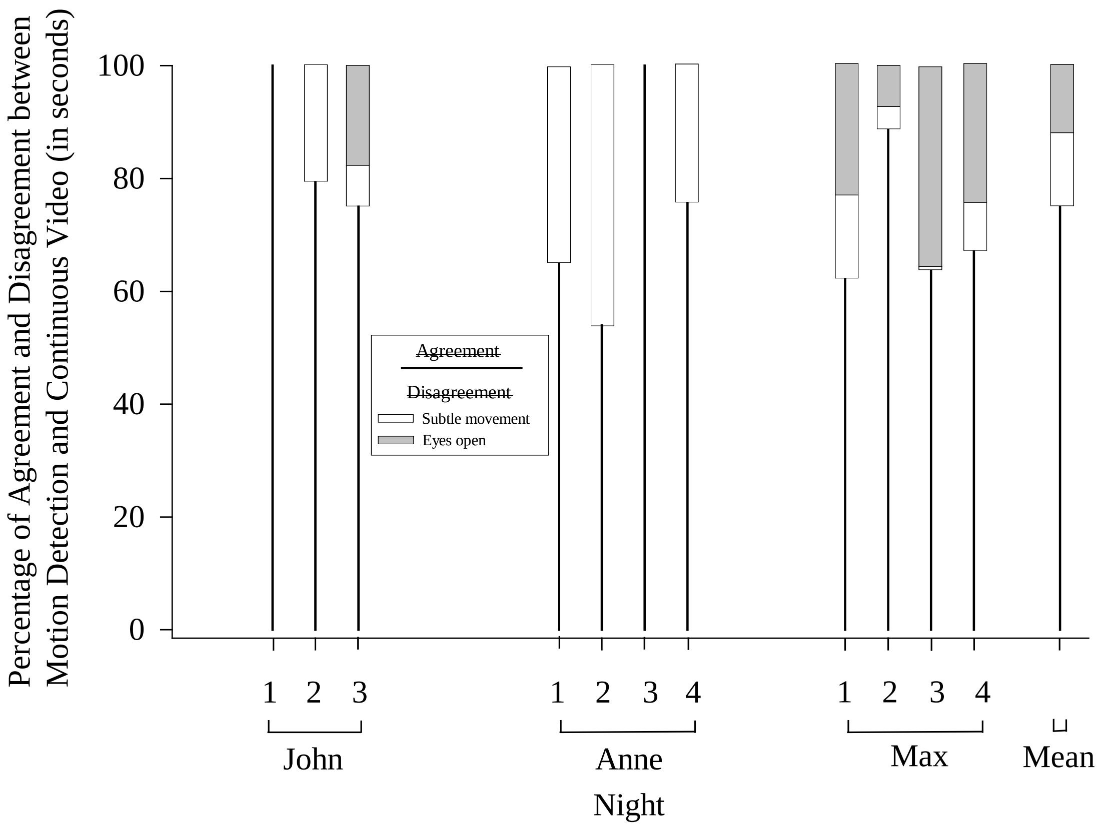

Figure 12. The y-axis depicts the percentage agreement and disagreement between the motion-detection camera and the criterion record. The primary x-axis shows all 11 nights and the mean for all 11 nights and the secondary x-axis denotes all three children. Line plots depict the percentage agreement and bar plots depict the topography of disagreement. The white and gray bars denote the disagreement comprised of subtle movement and eyes open, respectively.

To what extent did the accuracy of the MTS and actigraphy measurement systems compare to a continuous (second-by-second) measurement system? The same error analysis as for motion detection is depicted in the second and third columns of the first panel of Figure 11 for MTS 5- and MTS 10-min, respectively. We observed systematic overestimation of total sleep disturbance by a mean of 22 min (range, -5 to 39 min) for MTS 5-min and 32 min (range, 1 to 53 min) for MTS-10 min (second and third columns of the first panel in Figure 11). Actigraphy data showed the highest systematic overestimation, with a mean overestimation of 43 min (range, 12 to 77 min) across two children (fourth column of the first panel in Figure 11). Actigraphy data are only reported two children because one child did not tolerate wearing the device.

We observed overestimation with MTS-5, MTS-10 min and actigraphy for total sleep disturbance. When we analyzed the error for sleep onset latency for MTS 5-, MTS 10-min, and actigraphy the mean error was 1 (range, -8 to 3.5 min), 4 (range, -8 to 8 min), and -2 min (range, -16.5 to 4.5 min), respectively. Similar to motion detection, each measurement system indicated that the child initiated sleep at similar times as obtained with the continuous measurement system. For wakings after sleep onset, we observed systematic overestimation with a mean of 19 min (range, 3 to 33 min) for MTS 5, 24 min (range, 8 to 41 min) for MTS 10, and 44 min (range, 14 to 75 min) for actigraphy. The error values associated with motion detection, MTS 5-, MTS 10-min, and actigraphy for sleep onset latency and wakings after sleep onset indicated that most of the error for any measurement system occurred after the child initiated sleep. The likely reason why measures of sleep onset latency for all measurement systems closely align with the continuous measurement system is that the children were active for extended periods of time (e.g., physical movement, vocalizations, and object manipulation). This is particularly notable for motion detection and actigraphy which required the child to engage in behavioral quietude. The error for wakings after sleep onset is likely due to the short duration and distributed nature of the wakings and the children did not engage in the same activities as when initiating sleep (e.g., jumping in the bed).

The error data by type of sleep disturbance are important given that the prevalence of increased sleep onset latency as a primary sleep disturbance is approximately 51% for young children diagnosed with autism, 46% for children with developmental delay, and 30% for neurotypical children (Krakowiak, Goodlin-Jones, Hertz-Picciotto, Croen, & Hansen, 2008). The error data for wakings after sleep onset are also important because inaccuracies may limit one's conclusions about the severity of the disturbance during the assessment process.

Findings of systematic and unsystematic error is a known feature of partial-interval, momentary-time sampling procedures (Harrop & Daniels, 1986). Variables that influence this error include the duration between observation interval, duration of the observation interval, and the frequency and duration of the behavior (Powell, Martindale, & Kulp, 1975). Although we did not conduct formal analyses to determine which aspect of sleep disturbance was responsible for the error, we speculate that we observed systematic overestimation because intermittent bouts of awake of short duration were captured during the 5- or 10-min intervals. If the child was awake for extended durations during the night, we would expect less overestimation errors.

We also observed systematic overestimation with actigraphy. Actigraphy algorithms are calibrated against biological measures of awake obtained from polysomnography. We reviewed second-by-second data from actigraphy and compared those data to the data from the second-by-second continuous measurement system. The comparison suggested that both measurement systems showed the child as awake at similar times throughout the night. However, actigraphy showed longer durations of awake which may be a result of "extraneous movement" while transitioning from awake to sleep as hypothesized by Sitnick, Goodlin-Jones, and Anders (2008).

To what extent did the efficiency of the measurement systems compare to a

continuous (second-by-second) measurement system? Data on the time required to score total sleep disturbance throughout the night for all measurement systems are shown in the fourth panel of Figure 11. The y-axis depicts the time, in hours, to score total sleep disturbance for each night; the white bars represent the mean of the 11 nights and the data points indicate the individual nights for each child. The mean duration was 2.7 (range, 1 to 4.5 hr) for motion detection, 2.23 hr (range, 2 to 2.6 hr) for MTS 5-min, and 1.23 hr (range, 1 to 1.5 hr) for MTS 10-min. Researchers did not score sleep disturbance with actigraphy; the algorithm determined the amount of sleep disturbance, thus, the data are reported as a mean of 0 hr.

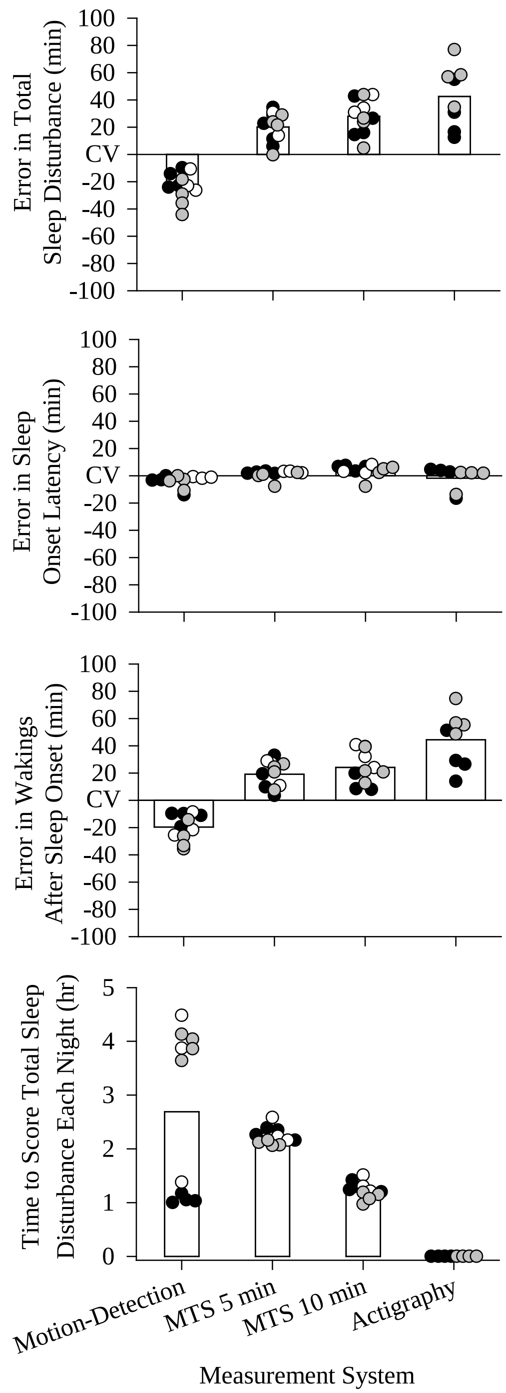

Figure 11. The panels depict summative data for all three children. The y-axes for the first three panels depict the mean difference from the continuous measurement system (i.e., second-by-second continuous video) in total sleep disturbance (top panel), sleep onset latency (middle panel), and waking after sleep onset (bottom panel) in min. The data in the fourth panel depict the total time to score total sleep disturbance in hr. The white bars represent the mean for each measurement system depicted on the x-axis. The white, black, and gray data points represent nightly values for John, Anne, and Max, respectively.

Using the continuous measurement system the mean time to score total sleep disturbance was about 13.0 hr (range of 11.0 to 14.5 hr [data not shown]). There was an improvement in the time score each night using the motion-detection measurement system; the mean was 2.7 hr with a range of 1 to 4.5 hr (a 65% decrease compared to scoring the night second-by-second). Although there was a drastic improvement in time to score the night using motion detection, there was notable variability insofar as five of the nights took just over 1 hr and six of the nights took more than 3.5 hr to score. These data present the issue of feasibility and may indicate motion detection as an unacceptable measurement system to score sleep on a daily, or even weekly, basis. One variable that influenced these measures includes the severity of sleep disturbance. That is, the more time the child is awake the more time that is required to score the night; this is most notable for two of the nights for John and all four nights for Max. In a related manner, the number of video clips per night also influenced the time to score each night. For Anne, the motion-detection camera produced 239, 246, 219, and 257 video clips across nights. For John, the motion-detection camera produced 381, 2,131, and 2,194 video clips across nights. For Max, the motion-detection camera produced 977, 915, 1,384, 1,142 clips across nights. We calibrated the camera to capture each instance of movement rather than bouts of movement, thus, when the child engaged in more movement, more video clips were produced which required more scoring time. Also, because we obtained descriptive measures of awake behavior the time to score was likely affected because we scored the exact second at which movement, vocalizations, or object manipulation occurred which may have required the data collector to rewind and review the specific timestamp more than once to ensure accurate timestamps.

Time to score sleep disturbance for motion detection and MTS 5- and MTS 10-min is directly affected by the duration of total sleep disturbance; more sleep disturbance requires more time to score. In fact, the children in this study exhibited a mean of 103 min (range, 44 to 194 min) of sleep onset latency which is within the range of the values for the seven children with an ASD reported by Wirojanan et al. (2009) and the 11 children with ASD, classified as poor sleepers, by Malow et al. (2006). These data suggest that time to score the night may not be affected with other children with an ASD because their sleep disturbance is likely to be more severe than their typical peer. The scoring procedures for motion detection make the measurement system inefficient because our data indicated that some nights require almost 5 hr of an observers' time to score the night. Thus, motion detection may not be reasonable to obtain nightly, or even weekly, measure of sleep disturbance. However, scoring sleep disturbance using motion detection may be more applicable during treatment because there would be less sleep disturbance rendering the measurement system more efficient. Because the motion-detection measurement system is accurate and involves direct observation, to retain these features, one potential solution to improve the time to score the night is to change the scoring rules. One option is to add the duration of all the video clips for a quantitative measure of sleep disturbance. We tested this solution and found that the duration of video clips did not equal the amount of sleep disturbance because when the child moved outside of the detection window, the camera did not detect movement. By adding the duration of clips, the value of direct-observation is lost, but another potential solution is to identify the time child is awake based on the file name of each video clip and use MTS to observe during that period of time. Thus, researchers should evaluate whether adding multiple detection windows would allow for simply adding the duration of clips to determine the amount of sleep disturbance. If this method provides accurate measures, researchers should also consider methods to sample representative data from the video clips to determine child behavior, social interactions, and qualitative features of the sleep environment.

Another option to obtain measures efficiently is to review the filename of the clips and use the rules that define sleep onset latency and wakings after sleep onset to determine total sleep disturbance. That is, the filename of the clips include the time at which movement occurred, thus, observers could simply review the inter-clip intervals to determine when 10 min have elapsed between video clips to determine sleep onset latency and sum the duration of clips after sleep onset latency to determine wakings after sleep onset latency. The data in Figure 13 depict our results using this solution. The y-axis depicts the hours of total sleep disturbance and the x-axis denotes nights for each child. The white and black bars represent the data obtained using the continuous and motion-detection measurement systems, respectively (these data are a re-depiction of the data presented in Figures 9 and 11). The gray bars represent data using this proposed scoring method for motion detection. For all nights, we recorded an increase in the hours of total sleep disturbance. The reason for the increase is because when motion is detected, a clip is produced. Thus, although we observed each clip using our formal scoring method, the seconds of movement may not be 10 consecutive seconds, therefore we did not score the child as awake. By using this proposed scoring method, these seconds are included in the duration of total sleep disturbance. Although this scoring method provides only a quantitative account of sleep disturbance, the video clips are available for direct observation of sleep disturbance. From an efficiency standpoint, in comparison to the 2.7 hr to obtain the data using motion detection with our formal scoring rules, this method required less than three minutes for each night, regardless of the severity of sleep disturbance. The results of this scoring method more closely approximated the amount of sleep disturbance captured from the continuous measurement system; this is a second reason why researchers should consider adding multiple detection windows to span the video feed to capture all movement that occurs in the bedroom, and perhaps the same levels of sleep disturbance would be recorded.

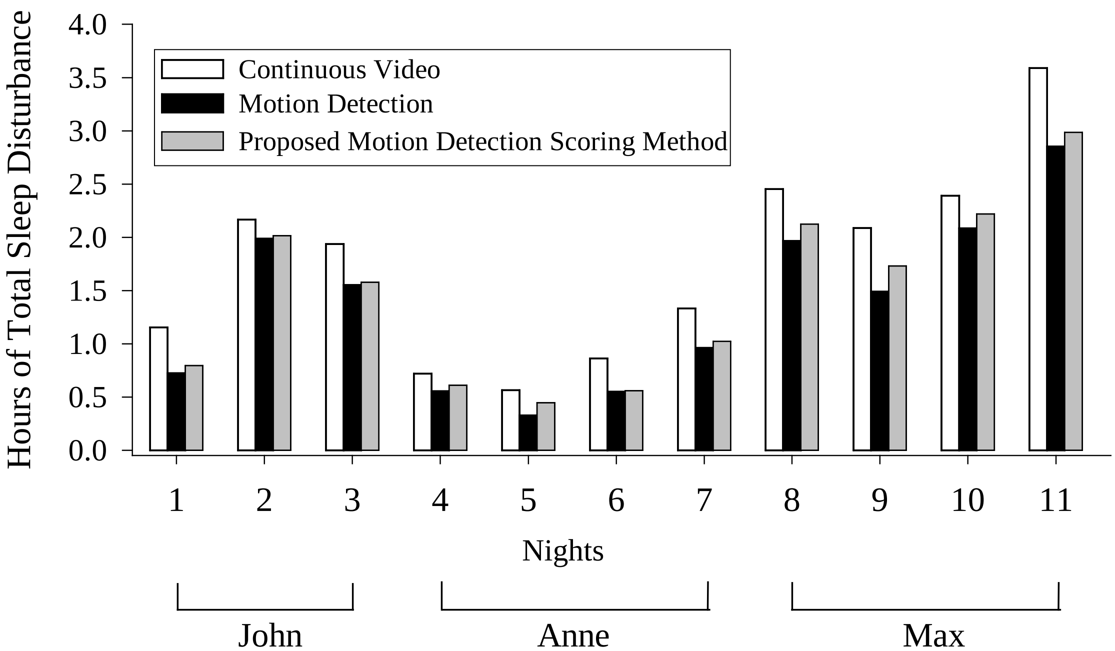

Figure 13. The y-axis depicts the hours of total sleep disturbance. The white bars represent data obtained from the second-by-second continuous measurement system, the black bars represent data obtained from the motion-detection measurement system and the gray bars represent data obtained using the proposed scoring method for the motion-detection measurement system.

Video cameras and actigraphy have been used to obtain in-home measures of sleep across decades of research but little is known about parents' acceptability of these data collection methods. Anne and Max's parent's report of social acceptability are depicted in Table 2. Because we did not obtain actigraphy data for John, his parent's reports of acceptability are not shown. Both parents strongly agreed with the acceptability of the nighttime video camera (*M* = 7) and actigraphy (*M* = 7). Their rankings, however, indicated that the nighttime video as most preferred. A noteworthy point is that John's mother did not report dissatisfaction with the nighttime video camera.

Table 2
Social Validity Questionnaire for Measurement Systems

Questions	Family 1: Mother of Anne	Family 3: Father of Max	*Mean*
Do you think *nighttime infrared video recording* (camera, infrared illuminator, and laptop) is acceptable for use in your home?	7 Not intrusive at all.	7 It wasn't in the way and it seemed necessary to collect accurate data.	7
Do you think *actigraphy* (placing the watch on your child and coordinating a time with the research team to download the data) is acceptable for use in your home?	7 We called it the "sleepytime watch" and felt like it served a dual purpose of providing you data as well as signaling that it was bedtime.	7 [Researcher] was very easy to work with and the watch was simple.	7
Please rank the measurement systems based on your preference (1 indicates the most preferred and 2 indicates the least preferred).	1. Nighttime infrared video recording 2. Actigraphy	1. Nighttime infrared video recording 2. Actigraphy	Nighttime infrared video recording

Note. The parents used a 7-point Likert scale with the following ratings: 7 = strongly agree, 4 = no opinion, 1= strongly disagree. Parents also provided open-ended answers for each question.

Obtaining accurate quantitative measures is one goal, but a more important goal is to learn about social interactions, child behavior, and qualitative features of the sleep environment; we evaluated the three direct-observation measurement systems that affords these benefits. Considering the accuracy and efficiency results, if we are to use a direct-observation measurement system, we recommend using MTS 10-min[7] because the accuracy measures match closely to those obtained from the second-by-second criterion record. Furthermore, the measurement system required less than 1.5 hr to obtain data for the entire night. The accuracy for MTS 5-min were similar to the accuracy data for MTS 10-min but MTS 10-min allowed a time savings of approximately 1 hr with regard to the time required to score the entire night. As applied in this study, MTS involved data collection only during the pre-determined observation intervals from which we obtained quantitative measures. To obtain qualitatively-rich information, the scoring rules may be adapted such that observers view before or after the 1-min observation interval for a glimpse of events that occur when the child is awake. Because it is accurate, motion detection, with multiple detection windows, may be a viable measurement system for researchers that choose to conduct descriptive analyses of events that occur throughout a night (Bijou, Peterson, & Ault, 1968; Thompson & Iwata, 2007).

The cost of the equipment may be an important variables for researchers and clinicians that assess and treat sleep disturbance. In this study, we used an Axis P1344 camera which cost $849.00 and about 2 hr of transfer time from the child's home. In clinical practice, however, we have been using Dropcam, a cloud-based video service to

[7] We also recommend the use of sleep diaries to complement video-based measures to account for sleep disturbance when the child is not in the bedroom or for daytime measures of sleep.

record and transfer videos. The Dropcam Pro is $199.00, requires a $99 storage fee, and the entire night downloads in about 10 min (see Supporting Information 1 and 2 for screenshots from the camera and technical details about each camera).

General Discussion

A direct-observation measurement system is most appropriate to measure sleep disturbance because it allows the observer to measure social interactions, which affects one's motivation to sleep, or identify environmental cues that are absent or have not been established as appropriate sleep dependencies (Blampied & France, 1993; Jin, Hanley, & Beaulieu, 2013). However, a direct-observation measurement system that yields inaccurate quantitative data negates the benefit of obtaining data regarding qualitative features in the sleep environment.

This series of studies extends sleep measurement research by providing an analog methodology to assess the precision of a motion-detection camera under a variety of conditions (Study 1) and assessing the generality of the methodology with human motor movements of varying sizes (Study 2). In Study 3, the comparison of four measurement systems that have been used to measure sleep disturbance to a continuous measurement system scored second-by-second supported that MTS 10 min produces accurate quantitative data in about 1 hr, and has the capacity to obtain data on qualitative features in the sleep environment. Although we do not recommend the motion-detection measurement system for nightly data collection, the camera settings are relevant to video analytic technology which involves the use of computer programs to analyze video streams. The advantage to video analytics is that a single video can be analyzed multiple times with different settings (e.g., object-size, sensitivity) to include movements of interest or exclude irrelevant movements. Our attempts to solicit expertise from leading companies that use video analytics were unsuccessful.

Although our primary focus was to determine which measurement system provides the opportunity to gather data on the social interactions or identification of stimuli that promote or prevent sleep initiation for behavioral sleep disturbance, video-based measures from the home have been used to screen for medically rooted sleep problems such as sleep apnea (Banhiran, Chotinaiwattarakul, Chongkolwatana, & Metheetrairut, 2014; Sivan, Kornecki, & Schonfeld, 1996). This application is particularly important because there may be severe consequences of sleep apnea that is not resolved with proper medical attention.

We evaluated the accuracy, time required to score sleep disturbance, and social validity with motion detection, MTS, and actigraphy. However, other measurement systems have been used to score sleep disturbance including time-lapse recording (e.g., Anders, Halpern, & Hua, 1992; Anders & Sostek, 1976; Ipsiroglu et al., 2015) and fast forwarding (Picciotto, Fuller, Hubbard, & McKenzie, 1998) but, comparisons of accuracy and interobserver agreement with a continuous (second-by-second) measurement system have not been conducted. The outcomes of these evaluations may provide the scientific community with accurate and efficient direct-observation alternatives to measure sleep disturbance.

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Appendix

Hardware Information

Product	Cost (US)	Specifications	Notes
Axis			
P1344 camera (current model is P1354)	$849.00	Resolution: 1280 X 720 pixels Angle-of-view: 27 – 66° Varifocal length: 3 – 8 mm Video compression: H.264 Security: Password, HTTPS encryption	The P1344 camera has been discontinued and replaced with the Axis P1354 camera. Information available at http://goo.gl/ZVjyUh.
T8123 High Power Over Ethernet Midspan	$89.00	Data rate: 10/100/1000 Mbps	A 12 hr video takes approximately 2 hr to transfer using LogMeIn Hamachi.
Axton AT-7 Infrared Illuminator (110°)	$339.00	Wavelength: 940 nm Illumination angle: 110°	
Nest			
Nest Cam	$199.00	Resolution: 1280 X 720 pixels Angle-of-view: 130° Video compression: H.264 Security: WEP, WPA, WPA2	Infrared illumination is built into the camera. The camera is powered via USB with a 5V power adapter (typically used to charge mobile devices). The camera can be viewed using iOS and Android mobile devices. A 12 hr video can be downloaded in 1 hr segments that take approximately 30 s to transfer from https://nest.com.

Note. These data were compiled following the conclusion of the study (June 2015).

Screenshots of camera view

Axis P1344:

Nest Cam: