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Assessment of Infant Movement With a Compact Wireless Accelerometer System

There is emerging data that patterns of motor activity early in neonatal life can predict impairments in neuromotor development. However, current techniques to monitor infant movement mainly rely on observer scoring, a technique limited by skill, fatigue, and inter-rater reliability. Consequently, we tested the use of a lightweight, wireless, accelerometer system that measures movement and can be worn by premature babies without interfering with routine care. We hypothesized that this system would be useful in assessing motor activity, in identifying abnormal movement, and in reducing the amount of video that a clinician would need to review for abnormal movements. Ten preterm infants in the NICU were monitored for 1 h using both the accelerometer system and video. A physical therapist trained to recognize cramped-synchronized general movements scored all of the video data by labeling each abnormal movement observed. The parameters of three different computer models were then optimized based on correlating features computed from accelerometer data and the observer's annotations. The annotations were compared to the model's prediction on unseen data. The trained observer identified cramped-synchronized general movements in 6 of the 10 infants. The computer models attained between 70% and 90% accuracy when predicting the same observer label for each data point. Our study suggests that mini-accelerometers may prove useful as a clinical tool assessing patterns of movement in preterm infants. [DOI: 10.1115/1.4006129]

Keywords: accelerometer, monitoring, infant movement, modeling

1 Introduction

The goal of this study was to begin to test the capability of minimally invasive, lightweight accelerometers to detect abnormal patterns of physical activity in prematurely born babies. Over the past two decades, the incidence and survival of preterm births (infants born at less than 37 weeks of gestation) have increased

dramatically [1]. Not surprisingly, long-term neuromotor complications often associated with prematurity such as cerebral palsy (CP) [2,3] or the less severe category of minor neurological dysfunction [4] have increased as well. Prematurity is also associated with seemingly paradoxical detriments to body composition later in life, namely, obesity, on the one hand, and growth retardation with osteopenia on the other [5–7]. These abnormalities are tied to impaired energy balance (the relationship between food intake and energy expenditure such as physical activity). The developing brain, nerves, and muscle early in life are remarkably plastic [8–11], as are the metabolic

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mechanisms that control body composition [12]. Recent data additionally show that the quality of motor activity early in life in preterm infants is associated with school-age intelligence [13]. The early assessment of physical activity patterns in premature babies is increasingly recognized as an essential step in identifying metabolic and/or neuromotor impairments and optimizing therapeutic approaches [14–18].

Given the fragility of this population and the constraints imposed on diagnostic procedures in premature babies, it is not surprising that early assessment of physical activity has proven to be quite challenging. Such measures depend almost exclusively on direct observation of infants, or on viewing post hoc, real-time videotape of infant activity [19,20]. Very little is known about the normal developmental patterns of physical activity in premature babies, and, as a consequence, identification of abnormalities can occur quite late. For example, it is generally agreed upon that the diagnosis of a condition like CP cannot be made definitively until a child is at least 4 years-old [3]. While sophisticated brain imaging such as MRI can provide additional anatomic mechanisms for conditions like CP [21], these approaches are not yet suited for screening and early diagnosis.

There has been limited research using accelerometers to monitor infant movement. Factors such as accelerometer weight and size, which are not problematic for physical activity measurement in older children [22,23], are major obstacles in premature babies. Accelerometers have been used in infants to assess sleep/wake cycles [24], more accurately assess the physiology of swallowing [25], and identify movements that could confound assessment of oxygen saturation derived from cutaneous monitors [26]. In addition, several studies conducted by Pickler et al. [27,28] have been done to examine preterm infant movement and sucking. Very few studies, however, have quantifiably measured infant limb movement and tied these movements with neurodevelopmental outcomes. Intriguingly, even using a large (4 g, $20 \times 12.5 \times 7.5$ mm) commercially available accelerometer placed on a single upper extremity, Ohgi et al. [29], in pioneering work, found different patterns of spontaneous movements of premature infants with known brain injuries compared with controls. In addition, promising research has recently been conducted by Heinze et al. [30] showing that a wired accelerometer could be used to differentiate between healthy babies and those at risk for cerebral palsy.

In order to optimize measurement and recording of spontaneous movements in premature babies, we recently developed an accelerometer small enough ($13 \times 10 \times 8$ mm) to be placed unobtrusively on all four extremities and the forehead of a premature infant and light enough (< 2 g) so that it would not interfere with spontaneous movement. In addition, the accelerometers are wireless, permitting real-time data acquisition and analysis [31]. Thus, we could measure the spontaneous movement of multiple extremities simultaneously.

As noted, a barrier in evaluating any new approach toward measuring infant movement is the dearth of metrics for comparison; however, in the case of the early diagnosis of CP, there exists a standardized, direct observation tool developed by Prechtl [32]. We designed the present experiments to compare our accelerometers with the Prechtl direct observational approach. In normal infants, Prechtl defined "general movements" (GMs) as elegant, smooth, variable in sequence, intensity and speed with a clear beginning and end. Prechtl also observed a unique abnormality of GMs that he named "cramped-synchronized" (CSGMs) in which the infant's limbs were rigid and moved nearly in synchrony. CSGMs have high predictive value for the development of cerebral palsy [33–35]. We hypothesized that the accelerometers developed specifically for prematurely born infants could accurately identify CSGMs.

2 Methods

This protocol was reviewed and approved by the Human Subjects Institutional Review Board at UCI. To identify potential participants, we screened the medical records of infants in the NICU

Table 1 Participant information. GA: gestational age

ID#	GA at birth	Birth Wt.	GA at monitoring
ID 1	28	1480	30
ID 2	25	860	36
ID 3	36	2150	37
ID 4	24	880	34
ID 5	26	765	36
ID 6	25	690	43
ID 7	26	800	35
ID 8	25	680	39
ID 9	28	1150	36
ID 10	28	1180	37
Average	27.1 weeks	1063.5 gm	36.3 weeks

at the UCI Medical Center and recruited preterm infants with a gestational age at birth of between 23 and 36 weeks. Infants were excluded if they had mothers less than age 18 or if they had skin disorders, which could preclude the attachment of the accelerometers to the skin). The parents of ten premature infants provided written informed consent and enrolled in the study. Information regarding the participants is provided in Table 1.

All infants were monitored and videotaped for 1 h at 30-43 weeks corrected gestational age (see Table 1) in their isolette wearing only a diaper and with all swaddling removed to allow for free limb movement. The ambient temperature of the isolette was adjusted and maintained according to the judgment of the NICU nurse. A video camera was positioned with a mid-sagittal view of the infant above the isolette at a downward angle of 45° to record motion for post hoc video scoring.

Five accelerometers were used for data collection. Each one measured three orthogonal axes of acceleration on the head and each of the four limbs. Devices were embedded in cloth bands that were placed around the wrists, ankles, and forehead of the infants with a canonical anatomical orientation.

2.1 Data Collection and Analysis. The accelerometers transmitted data that was sampled nonuniformly at approximately 19 Hz in real-time to a computer located nearby. The raw accelerometer data consisted of real valued samples of the three axes measuring the degree of acceleration due to gravity and changes in limb motion. Although data was collected from four limbs and the forehead, subsequent analysis demonstrated that head movement did not substantially vary and was excluded from further analysis.

2.2 Data Annotation. The collected video data was annotated based on the visual observation technique developed by Prechtl et al. for identifying CSGMs. A NICU physical therapist, trained in the assessment, identified windows of time in the video in which the infants demonstrated CSGMs. The physical therapist annotated start and stop time for each CSGM observed. It is important to note that this physical therapist was employed at a different NICU, had no clinical contact with participants in the study and was masked to the infant's medical history and age. This scoring technique provided a binary label for every time sample of either "CSGM Observed" or "CSGM Not Observed." The annotated data was then synchronized with the corresponding timestamps in the video and accelerometer data.

2.3 Accelerometer Data Processing. The raw accelerometer data was collected at 19 Hz and was indexed by a time stamp. Each time stamp had associated with it 12 values corresponding to three axes of acceleration data collected for each of four limbs. This raw data required significant cleaning and processing to support effective modeling. The result of the data processing was to create 166 values associated with each time stamp. These were "features" that could be correlated with video observations at the
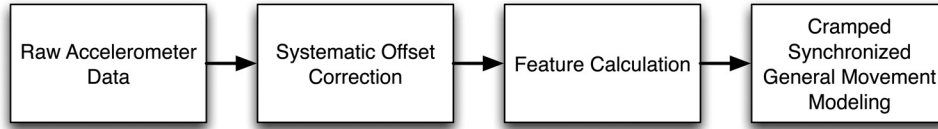
Fig. 1 Dataflow diagram

same time stamp and were the bases of the CSGM modeling (see Fig. 1).

There were three primary artifacts in our raw data that needed to be accounted for in our preprocessing. The first was that the data was not collected at uniform intervals. Although each reading was accurately time-stamped, the sampling frequency was irregularly spaced with a 19 Hz average. This made calculating features based on frequency analysis outside the scope of this study. The second was that every triple of accelerometer readings contained a 1-g component due to gravity, which was indistinguishable from a 1-g change in movement in a baby. Based on the orientation of the baby's limbs this component was distributed across the three axes in different proportions at different times. The third was that there were periods of time in our collected data in which various NICU medical interventions invalidated a few seconds of our data. The impact of these artifacts was reduced as follows:

We manually identified periods of time in which the accelerometer data was not generated by spontaneous movements in the baby by reviewing the video. Examples of situations like this included pacifier adjustments by the NICU nurses, bumping of the isolette during temperature adjustments, and adjustments to the monitoring equipment. Removing this data resulted in gaps in the data stream that were conceptually similar to the already irregularly collected data samples although they were an order of magnitude larger. Each baby subsequently had a different absolute number of data points N that nonetheless spanned an hour.

To eliminate systematic biases in the readings that were not related to motion, such as gravity and sensor calibration drift, we filtered out low frequency accelerations by subtracting the the mean of a 10 s window centered on each data point. This is comparable to the removal of the DC component of the FFT used by Bao and Intille [36] given that regular samples were not available. The low frequency filtering equations are as follows:

$$t'_{i,j} = t_{i,j} - m_{i,j} \quad [i \in 1:N, j \in x, y, z]$$
$$m_{i,j} = mean\,(t_{k,j}) \quad [i - 5s : k : i + 5s] \tag{1}$$

For every sample time i and every axis j, we subtracted from the observed data point, $t_{i,j}$, the mean of a 10 s window centered at time i. The number of data points over which the mean was calculated was not constant because the data was collected at nonuniform intervals and because some data was removed due to intervention. However, the mean was calculated over the same *duration* of time. This process served to eliminate the effect of gravity and any other systematic constant offset in our readings (e.g., calibration drift) without reducing the number of data points.

In this study, we did not model the posture of the baby, only the changes in the motion of the limbs, so we subsequently merged the three axes from each accelerometer into a single value that captured the overall magnitude of the smoothed data. For each time stamp, this resulted in four new data values, one that aggregated the motion from each limb. These were the first four features and represented the "corrected acceleration magnitude,"

$$F_i^L = \sqrt{(t'_{i,x})^2 + (t'_{i,y})^2 + (t'_{i,z})^2}$$
$$i \in 1:N \tag{2}$$
$$L \in \{\text{left arm, right arm, left leg, right leg}\}$$

One of the motivations for this method of data preprocessing (as opposed to aggregating over nonoverlapping temporal windows) was to ensure that the number of data points was not reduced so that they could be matched to the video annotations with high temporal fidelity.

2.4 Feature Extraction. From the smoothed stream of accelerometer data, we next extracted statistical features for analysis. The features chosen were based on a desire to capture aspects of CSGMs specifically and general movements of the limbs more broadly.

We calculated the following instantaneous sample-based features for each data point:
● Maximum values of the corrected acceleration magnitude of the upper and lower body

$$F_i^5 = \max(F_i^{\text{left-arm}}, F_i^{\text{right-arm}})$$
$$F_i^6 = \max(F_i^{\text{left-leg}}, F_i^{\text{right-leg}})$$

● Maximum of all the limbs

$$F_i^7 = \max(F_i^{\text{left-arm}}, F_i^{\text{right-arm}}, F_i^{\text{left-leg}}, F_i^{\text{right-leg}})$$

● Product of the corrected magnitude of the upper and lower body

$$F_i^8 = F_i^{\text{left-arm}} * F_i^{\text{right-arm}}$$
$$F_i^9 = F_i^{\text{left-leg}} * F_i^{\text{right-leg}}$$

● Product of the corrected magnitude of the total body

$$F_i^{10} = F_i^{\text{left-arm}} * F_i^{\text{right-arm}} * F_i^{\text{left-leg}} * F_i^{\text{right-leg}}$$

After these initial ten features, we also calculated several features based on functions that aggregated over windows of time: the mean, the maximum, the minimum, the standard deviation, and the z-value. The time windows we used covered 1 s, 2 s, or 4 s centered on the current data point. The data that we aggregated over included each of the first ten features. This resulted in an additional 150 features (See Table 2).

The final six features that we calculated were the Pearson correlation between the left and right arm and the right and left leg. Although the correlation was for a single pair of data points, we used the same three windows as above to calculate the aggregate statistics required for each Pearson correlation calculation.

$$F_i^{\{161,162,163\}} = Correl_{\{1s,2s,4s\}}(F_i^{\text{left-arm}}, F_i^{\text{right-arm}})$$
$$F_i^{\{164,165,166\}} = Correl_{\{1s,2s,4s\}}(F_i^{\text{left-leg}}, F_i^{\text{right-leg}})$$

Table 2 Temporal feature calculation components

Function	mean, maximum, minimum, standard deviation, z-value
Window Length	1 s, 2 s, 4 s
Data	$F^{\text{left-arm}}, F^{\text{right-arm}}, F^{\text{left-leg}}, F^{\text{right-leg}}, F^5, F^6, F^7, F^8, F^9, F^{10}$

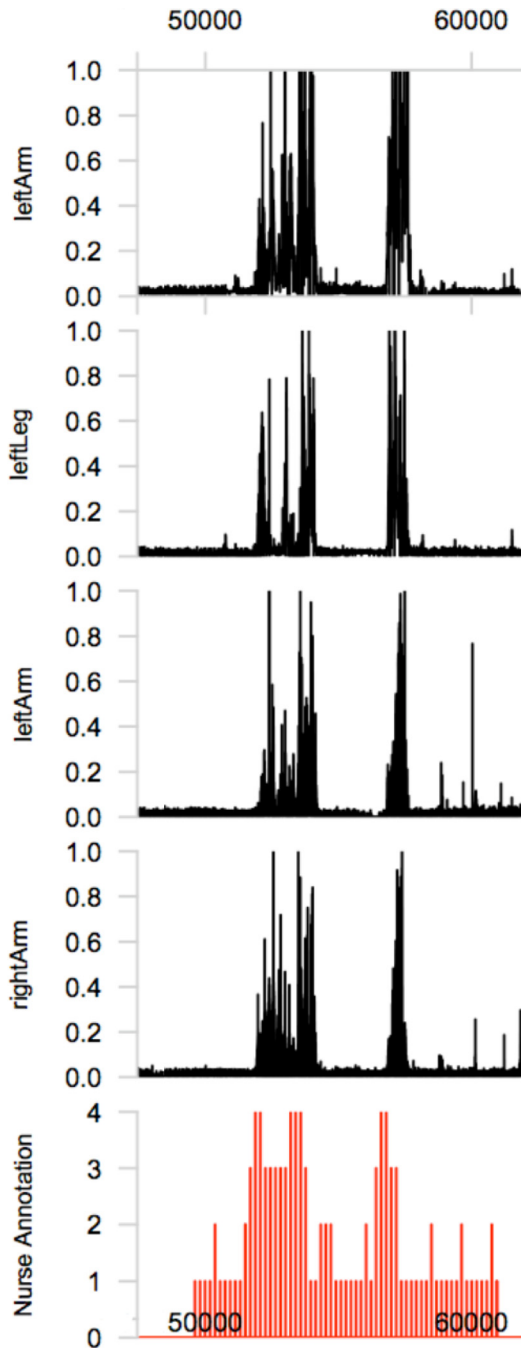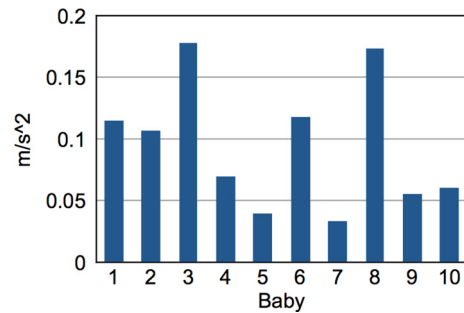Fig. 3 Average corrected acceleration magnitude over 1 h

dom forests [37]. Each technique utilized cross-validation on a baby-by-baby basis in which a model was trained on one baby and tested on the other nine babies' data. During testing, the first two techniques are presented with feature vectors in isolation. The DBN is presented with the complete temporal series of feature vectors for each training set. In all cases, the test data is withheld while training. Each algorithm chooses a classification for each sample based on its respective algorithm.

3 Results

In order to validate our experimental setup and the accelerometers' ability to perform movement assessments, we first conducted an analysis in which a nurse scored the videos for periods of infant activity. Using the four-point Giganti scale [20], we had a nurse annotate the video data at 110 time points throughout the hour of data. Fifty annotations were made at the top of every minute for 50 min, and 60 annotations were made every ten seconds for the remaining 10 min. Visual and statistical analysis demonstrated high correlation between the nurse's labels and the raw data. A portion of the data is shown in Fig. 2. Ten minutes of data from the four limbs are shown in the top four graphs black with the nurse's scoring in red in the bottom graph.

The average overall corrected acceleration magnitude for allinfants was 0.095 m/s^2, with anaverage corrected arm acceleration of 0.11 m/s^2 and average corrected leg acceleration of 0.08 m/s^2. The maximum arm acceleration noted in any infant was 3.80 m/s^2, and the maximum leg acceleration was 3.87 m/s^2. Figure 3 shows the average corrected acceleration for each baby over the entire 1 h observation period (average across all times of the average of four limbs at each time sample). A wide range of average accelerations reflected wide variability in baby motion. Figure 4 shows the Pearson correlation calculated between the arms and
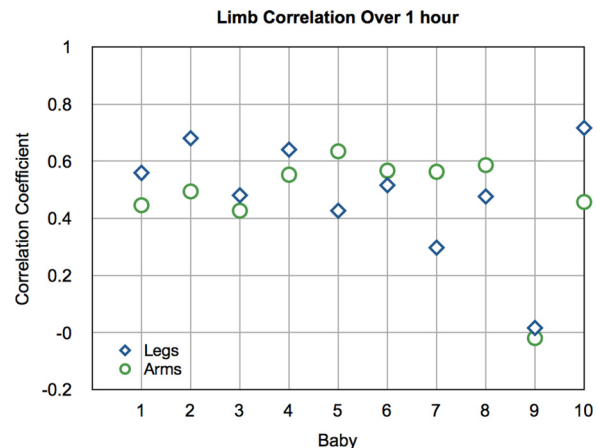

Fig. 2 Approximately 10 min of Giganti activity coding. Corrected accelerometer readings for the four limbs of one baby are shown in the top four graphs. The nurse's annotation of the data from sample 50,000 to 60,000 is shown in the bottom graph.

2.5 Modeling Prechtl Cramped-Synchronized General Movements. The target classifications that we modeled were taken from the start and stop times that the trained physical therapist marked when observing CSGMs. The feature vector for each data point consisted of a total of 166 features, derived from both instantaneous data and temporal features as described above. The physical therapist's annotations provided a binary target class for each feature vector that was the value that we were trying to model and predict.

To predict the class we utilized three statistical machine learning techniques: support vector machines (SVMs), decision trees, and dynamic Bayesian networks observing the output from ran-

Fig. 4 Pearson correlation for upper and lower extremities for each baby

Fig. 5 Scatter plot comparing the maximum corrected acceleration for arms versus legs for each baby
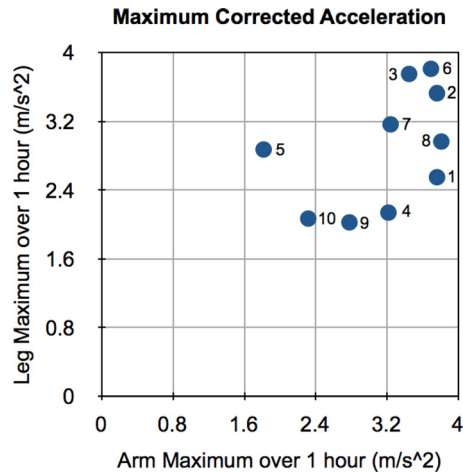

Fig. 6 Scatter plot comparing the average corrected acceleration for arms versus legs for each baby

between the legs of each baby. The right arm and left arm had an average correlation coefficient of 0.47, with 1 being perfectly correlated and 0 being no correlation. The right leg and left leg had an average correlation coefficient of 0.48. Figures 5 and 6 show a scatter plot of the arm and leg acceleration observed and the average corrected acceleration observed. A strong correlation is seen between arm and leg acceleration.

3.1 Prechtl Movement Results. The physical therapist identified 102 total CSGMs in six of the ten infants in the study. Each baby generated approximately 70,000 data points for a total of approximately 700,000 samples in our data. Using tenfold cross-validation, we applied the three algorithms to the data. Each technique produced different results that traded off sensitivity and specificity. Accuracies ranged from 70-90% and achieved an average sensitivity of 99.2% and an average specificity of 99.6%. Detailed measurements are shown in Table 3.

We conducted an analysis of the most informative features that were identified by the decision tree modeling. For each decision tree that was created in each of the ten cross validation folds, we ranked the features according to their independent information gain to identify which single feature was the most correlated with CSGMs. For each feature we averaged the rank across the ten trees. Table 4 shows the results.

The most informative feature was the minimum across a 2 s window of the maximum acceleration magnitude of all limbs for a given sample. This demonstrates that recognizing CSGMs requires observing a sustained motion. CSGMs are not particularly high-energy motions, however, and this suggests that normal
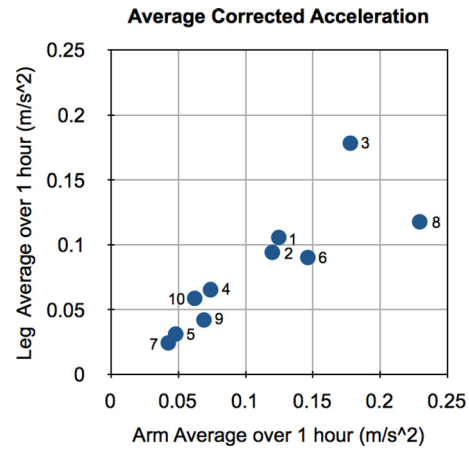
motions do not sustain a continuously observed acceleration on all limbs for an entire 2 s window. The next nine most informative features were based on recognizing peak accelerations. This suggests that the sensor signature of CSGMs has sudden stops and starts although the movement itself is not characterized by a lot of high frequency motion. Finally, two of the top four features were correlated with the right side of the body. This is a curious result, but retrospective analysis of the cohorts medical records indicates that the majority of the patients had left side hemorrhaging that was apparently manifesting in right side motion.

4 Discussion

The diagnosis of neuromotor abnormalities in children, as well as the assessment of patterns of physical activity early in life, has traditionally rested on observation by physicians, skilled health care professionals, or parents [38,39]. Advances have been made in a variety of such approaches including tools such as the Test of Infant Motor Performance [40], the Alberta Infant Motor Scale [41], and the Infant Motor Profile [42]. However, these approaches are tedious, rely on skilled observers, require substantial time for observation and analysis, and are subject to substantial errors due to inter-rater reliability. Moreover, direct observations of human energy expenditure have been found to be limited to 3 s intervals of activity and to no more than 20 min of direct observation (before observer fatigue becomes problematic) [43]. Given the rapid and sporadic nature of physical activity in premature babies, direct observation of physical activity profiles has serious limitations.

In this study, we were able to successfully implement infant accelerometer monitoring in the NICU. We were able to

Table 3 Modeling results

Baby ID	CSGM present	Decision tree		SVM		DBN + random forest	
		Sensitivity	Specificity	Sensitivity	Specificity	Sensitivity	Specificity
1	No	–	0.894	–	*	–	0.490
2	Yes	0.089	0.957	0.087	0.945	0.512	0.781
3	No	–	0.864	–	*	–	0.420
4	Yes	0.137	0.965	0.082	0.964	0.459	0.793
5	Yes	0.092	0.967	0.037	0.986	0.611	0.906
6	Yes	0.092	0.967	0.043	0.976	0.414	0.788
7	Yes	0.057	0.969	0.069	0.984	0.575	0.800
8	Yes	0.212	0.830	0.147	0.914	0.760	0.394
9	No	–	0.979	–	*	–	0.737
10	No	–	0.957	–	*	–	0.822
Average	–	0.103	0.939	0.069	0.964	0.498	0.764

Note: Algorithmic limitations (*) and lack of true positives (-) prevented some entries from being calculated.

Table 4 Average ranking of features according to information gain

min (max (all limbs))	2.17
max (right arm)	3.67
max (product (both arms))	4.25
max (right leg)	4.5
max (left leg)	4.67
max (max (both legs))	5
max (product (both legs))	5.5
max (max (both arms))	6.5
max (max (all limbs))	7.3
max (left arm)	8
min (max (both arms))	10.5

characterize limb acceleration and measure limb correlation. We were also successful in creating a model for CSGMs using acceleration-only data with high accuracy and specificity. In addition, we confirmed our results with three separate statistical machine learning techniques. While the methods used in this paper cannot eliminate medical observation, they have the promise for greatly reducing the amount of video required to be analyzed by a trained expert.

This study was limited by a small sample size of ten infants, and therefore our data's generalizability is limited. However, the data dense accelerometer was able to capture thousands of data points during the 1 h monitoring session, in some cases over 70,000 per infant. A possible confounding factor in the data was that CSGMs were identified only in the infants weighing less than 1000 g at birth and born at less than 27 weeks gestation. While curious, our analysis was performed on each sample with algorithms that were blinded to which baby the sample came from. The impact of this correlation should have been negligible on our approach. In addition, these babies are at the highest risk for CP and, therefore, increased prevalence of CSGMs is expected. In addition, our data was annotated by only a single physical therapist and, therefore, our model is limited by her perceptions of infant movement. However, our results suggest that the masked physical therapist was consistent in her scoring system for CSGMs because we were able to predict her scores with extremely high accuracy.

In contrast to the work by Ohgi et al., our work examined a full hour of data collected from four limbs instead of 200 s of data from a single arm. Since our data was transmitted wirelessly in real-time it is more suitable to clinical applications and potential real-time feedback. Correspondingly, our data sample rate was nonuniform and an order of magnitude slower. As our focus was on using the data for clinical evaluation of CGSMs as opposed to analyzing the degree of randomness in the motion, this proved to be sufficient.

This is the first study to our knowledge that attempts to automate scoring for cramped synchronized general movements. Lightweight accelerometers may be useful as clinical tools to assess abnormal patterns of motor activity in preterm infants. Early prediction of CP through the use of an automated device could lead to early treatment and prevention strategies. In addition, this novel technique has the potential for expansion to detection of other neuromotor disorders such as seizures, intraventricular hemorrhage, or autism.

Acknowledgment

References

[1] Ashton, D. M., Lawrence, H. C., III, Adams, N. L., III, and Fleischman, A. R., 2009, "Surgeon General's Conference on the Prevention of Preterm Birth," Obstet. Gynecol., **113**(4), pp. 925–930.

[2] Babcock, M. A., Kostova, F. V., Ferriero, D. M., Johnston, M. V., Brunstrom, J. E., Hagberg, H., and Maria, B. L., 2009, "Injury to the Preterm Brain and Cerebral Palsy: Clinical Aspects, Molecular Mechanisms, Unanswered Questions, and Future Research Directions," J. Child Neurol., **24**(9), pp. 1064–1084.

[3] Krageloh-Mann, I., and Cans, C., 2009, "Cerebral Palsy Update," Brain Dev., **31**(7), pp. 537–544.

[4] Hadders-Algra, M., Heineman, K. R., Bos, A. F., and Middelburg, K. J., 2010, "The Assessment of Minor Neurological Dysfunction in Infancy Using the Touwen Infant Neurological Examination: Strengths and Limitations," Dev. Med. Child Neurol., **52**(1), pp. 87–92.

[5] Dusick, A. M., Poindexter, B. B., Ehrenkranz, R. A., and Lemons, J. A., 2003, "Growth Failure in the Preterm Infant: Can We Catch Up?," Semin. Perinatol., **27**(4), pp. 302–310.

[6] Land, C., and Schoenau, E., 2008, "Fetal and Postnatal Bone Development: Reviewing the Role of Mechanical Stimuli and Nutrition," Best Pract. Res. Clin. Endocrinol. Metab., **22**(1), pp. 107–118.

[7] Greer, F. R., 2007, "Long-Term Adverse Outcomes of Low Birth Weight, Increased Somatic Growth Rates, and Alterations of Body Composition in the Premature Infant: Review of the Evidence," J. Pediatr. Gastroenterol. Nutr., **45**(Suppl. 3), pp. S147–S151.

[8] Staudt, M., 2010, "Brain Plasticity Following Early Life Brain Injury: Insights From Neuroimaging," Semin. Perinatol., **34**(1), pp. 87–92.

[9] Tillakaratne, N. J., Guu, J. J., de Leon, R. D., Bigbee, A. J., London, N. J., Zhong, H., Ziegler, M. D., Joynes, R. L., Roy, R. R., and Edgerton, V. R., 2010, "Functional Recovery of Stepping in Rats After a Complete Neonatal Spinal Cord Transection is Not Due to Regrowth Across the Lesion Site," Neuroscience, **166**(1), pp. 23–33.

[10] Fisher, T., and Clowry, G. J., 2009, "Elimination of Muscle Afferent Boutons From the Cuneate Nucleus of the Rat Medulla During Development," Neuroscience, **161**(3), pp. 787–793.

[11] Matsakas, A., and Patel, K., 2009, "Skeletal Muscle Fibre Plasticity in Response to Selected Environmental and Physiological Stimuli," Histol. Histopathol., **24**(5), pp. 611–629.

[12] Beardsall, K., and Dunger, D., 2008, "Insulin Therapy in Preterm Newborns," Early Hum. Dev., **84**(12), pp. 839–842.

[13] Bruggink, J. L., Van Braeckel, K. N., and Bos, A. F., 2010, "The Early Motor Repertoire of Children Born Preterm is Associated With Intelligence at School Age," Pediatrics, **125**(6), pp. e1356–e1363.

[14] Casey, P. H., Bradley, R. H., Whiteside-Mansell, L., Barrett, K., Gossett, J. M., and Simpson, P. M., 2009, "Effect of Early Intervention on 8-Year Growth Status of Low-Birth-Weight Preterm Infants," Arch. Pediatr. Adolesc. Med., **163**(11), pp. 1046–1053.

[15] Majnemer, A., 1998, "Benefits of Early Intervention for Children With Developmental Disabilities," Semin. Pediatr. Neurol., **5**(1), pp. 62–69.

[16] Groen, S. E., de Blecourt, A. C., Postema, K., and Hadders-Algra, M., 2005, "General Movements in Early Infancy Predict Neuromotor Development at 9 to 12 Years of Age," Dev. Med. Child Neurol., **47**(11), pp. 731–738.

[17] Cameron, E. C., Maehle, V., and Reid, J., 2005, "The Effects of an Early Physical Therapy Intervention for Very Preterm, Very Low Birth Weight Infants: A Randomized Controlled Clinical Trial," Pediatr. Phys. Ther., **17**(2), pp. 107–119.

[18] Blauw-Hospers, C. H., and Hadders-Algra, M., 2005, "A Systematic Review of the Effects of Early Intervention on Motor Development," Dev. Med. Child Neurol., **47**(6), pp. 421–432.

[19] Giganti, F., Ficca, G., Gori, S., and Salzarulo, P., 2008, "Body Movements During Night Sleep and Their Relationship With Sleep Stages are Further Modified in Very Old Subjects," Brain Res. Bull., **75**(1), pp. 66–69.

[20] Giganti, F., Cioni, G., Biagioni, E., Puliti, M. T., Boldrini, A., and Salzarulo, P., 2001, "Activity Patterns Assessed Throughout 24-Hour Recordings in Preterm and Near Term Infants," Dev. Psychobiol., **38**(2), pp. 133–142.

[21] Korzeniewski, S. J., Birbeck, G., DeLano, M. C., Potchen, M. J., and Paneth, N., 2008, "A Systematic Review of Neuroimaging for Cerebral Palsy," J. Child Neurol., **23**(2), pp. 216–227.

[22] Cliff, D. P., Reilly, J. J., and Okely, A. D., 2009, "Methodological Considerations in Using Accelerometers to Assess Habitual Physical Activity in Children Aged 0-5 Years," J. Sci. Med. Sport, **12**(5), pp. 557–567.

[23] Rowlands, A. V., 2007, "Accelerometer Assessment of Physical Activity in Children: An Update," Pediatr. Exerc. Sci., **19**(3), pp. 252–266.

[24] So, K., Adamson, T. M., and Horne, R. S., 2007, "The Use of Actigraphy for Assessment of the Development of Sleep/Wake Patterns in Infants During the First 12 Months of Life," J. Sleep Res., **16**(2), pp. 181–187.

[25] Reynolds, E. W., Vice, F. L., Bosma, J. F., and Gewolb, I. H., 2002, "Cervical Accelerometry in Preterm Infants," Dev. Med. Child Neurol., **44**(9), pp. 587–592.

[26] Rimet, Y., Brusquet, Y., Ronayette, D., Dageville, C., Lubrano, M., Mallet, E., Rambaud, C., Terlaud, C., Silve, J., Lerda, O., Netchiporouk, L. I., and Weber, J. L., 2007, "Surveillance of Infants at Risk of Apparent Life Threatening Events (ALTE) With the BBA Bootee: A Wearable Multiparameter Monitor," Conf. Proc. IEEE Eng. Med. Biol. Soc., pp. 4997–5000.

[27] Pickler, R. H., Best, A. M., Reyna, B. A., Gutcher, G., and Wetzel, P. A., 2006, "Predictors of Nutritive Sucking in Preterm Infants," J. Perinatol., **26**(11), pp. 693–699.

[28] Pickler, R. H., Best, A. M., Reyna, B. A., Wetzel, P. A., and Gutcher, G. R., 2005, "Prediction of Feeding Performance in Preterm Infants," Newborn Infant Nurs. Rev., **5**(3), pp. 116–123.

[29] Ohgi, S., Morita, S., Loo, K. K., and Mizuike, C., 2008, "Time Series Analysis of Spontaneous Upper-Extremity Movements of Premature Infants With Brain Injuries," Phys. Ther., **88**(9), pp. 1022–1033.

[30] Heinze, F., Hesels, K., Breitbach-Faller, N., Schmitz-Rode, T., and Disselhorst-Klug, C., 2010, "Movement Analysis by Accelerometry of Newborns and Infants for the Early Detection of Movement Disorders Due to Infantile Cerebral Palsy," Med. Biol. Eng. Comput., **48**(8), pp. 765–772.

[31] Park, C., and Chou, P. H., "Ultra-Wearable and Expandable Wireless Sensor Platform," 2006, Proceedings Third International Workshop on Body Sensor Networks, pp. 162–165.

[32] Prechtl, H. F., 1997, "State of the Art of a New Functional Assessment of the Young Nervous System. An Early Predictor of Cerebral Palsy," Early Hum. Dev., **50**(1) pp. 1–11.

[33] Ferrari, F., Cioni, G., Einspieler, C., Roversi, M. F., Bos, A. F., Paolicelli, P. B., Ranzi, A., and Prechtl, H. F., 2002, "Cramped Synchronized General Movements in Preterm Infants as an Early Marker for Cerebral Palsy," Arch. Pediatr. Adolesc. Med., **156**(5), pp. 460–467.

[34] Cioni, G., Ferrari, F., Einspieler, C., Paolicelli, P. B., Barbani, M. T., and Prechtl, H. F., "Comparison Between Observation of Spontaneous Movements and Neurologic Examination in Preterm Infants," J. Pediatr., **130**(5), pp. 704–711.

[35] Prechtl, H. F., Einspieler, C., Cioni, G., Bos, A. F., Ferrari, F., and Sontheimer, D., 1997, "An Early Marker for Neurological Deficits After Perinatal Brain Lesions," Lancet, **349**(9062), pp. 1361–1363.

[36] Bao, L., and Intille, S., 2004, "Activity Recognition From User-Annotated Acceleration Data," Pervasive Computing, A. Ferscha and F. Mattern, eds., Springer, Berlin, pp. 1–17.

[37] Breiman, L., 2001, "Random Forests," Mach. Learn., **45**(1), pp. 5–32.

[38] Donohue, P. K., and Graham, E. M., 2007, "Earlier Markers for Cerebral Palsy and Clinical Research in Premature Infants," J. Perinatol., **27**(5), pp. 259–261.

[39] Ehrmann, F. D., Couture, M., Grilli, L., Simard, M. N., Azoulay, L., and Gosselin, J., 2005, "When and by Whom is Concern First Expressed for Children With Neuromotor Problems?," Arch. Pediatr. Adolesc. Med., **159**(9), pp. 882–886.

[40] Campbell, S. K., Kolobe, T. H., Wright, B. D., and Linacre, J. M., 2002, "Validity of the Test of Infant Motor Performance for Prediction of 6-, 9- and 12-Month Scores on the Alberta Infant Motor Scale," Dev. Med. Child Neurol., **44**(4), pp. 263–272.

[41] Darrah, J., Senthilselvan, A., and Magill-Evans, J., 2009, "Trajectories of Serial Motor Scores of Typically Developing Children: Implications for Clinical Decision Making," Infant Behav. Dev., **32**(1), pp. 72–78.

[42] Heineman, K. R., la Bastide-van Gemert, S., Fidler, V., Middelburg, K. J., Bos, A. F., and Hadders-Algra, M., 2010, "Construct Validity of the Infant Motor Profile: Relation With Prenatal, Perinatal, and Neonatal Risk Factors," Dev. Med. Child Neurol., **52**(9), pp. e209-e215.

[43] Bailey, R. C., Olson, J., Pepper, S. L., Barstow, T. J., Porszsasz, J., and Cooper, D. M., 1995, "The Level and Tempo of Children's Physical Activities: An Observational Study," Med. Sci. Sports Exercise, **27**, pp. 1033–1041.